# The Unreasonable Effectiveness of Deep Learning

## Deep Learning — Unit 1

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Slides available at jonkrohn.com/talks

July 21st, 2018

1. Name
2. Relevant background, e.g., programming, stats, machine learning
3. Interest in Deep Learning
4. What you'd like to take away from this course

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# Outline

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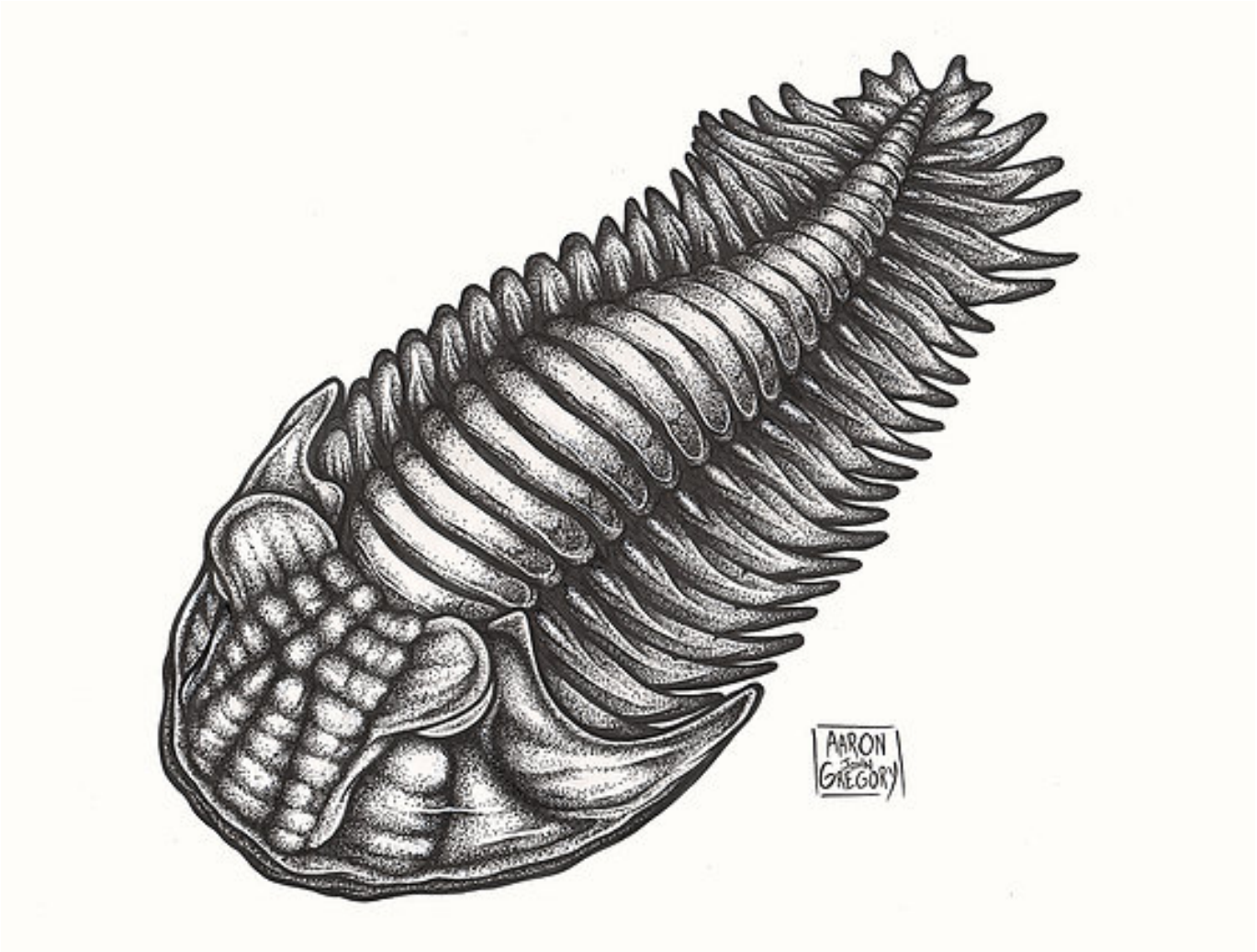
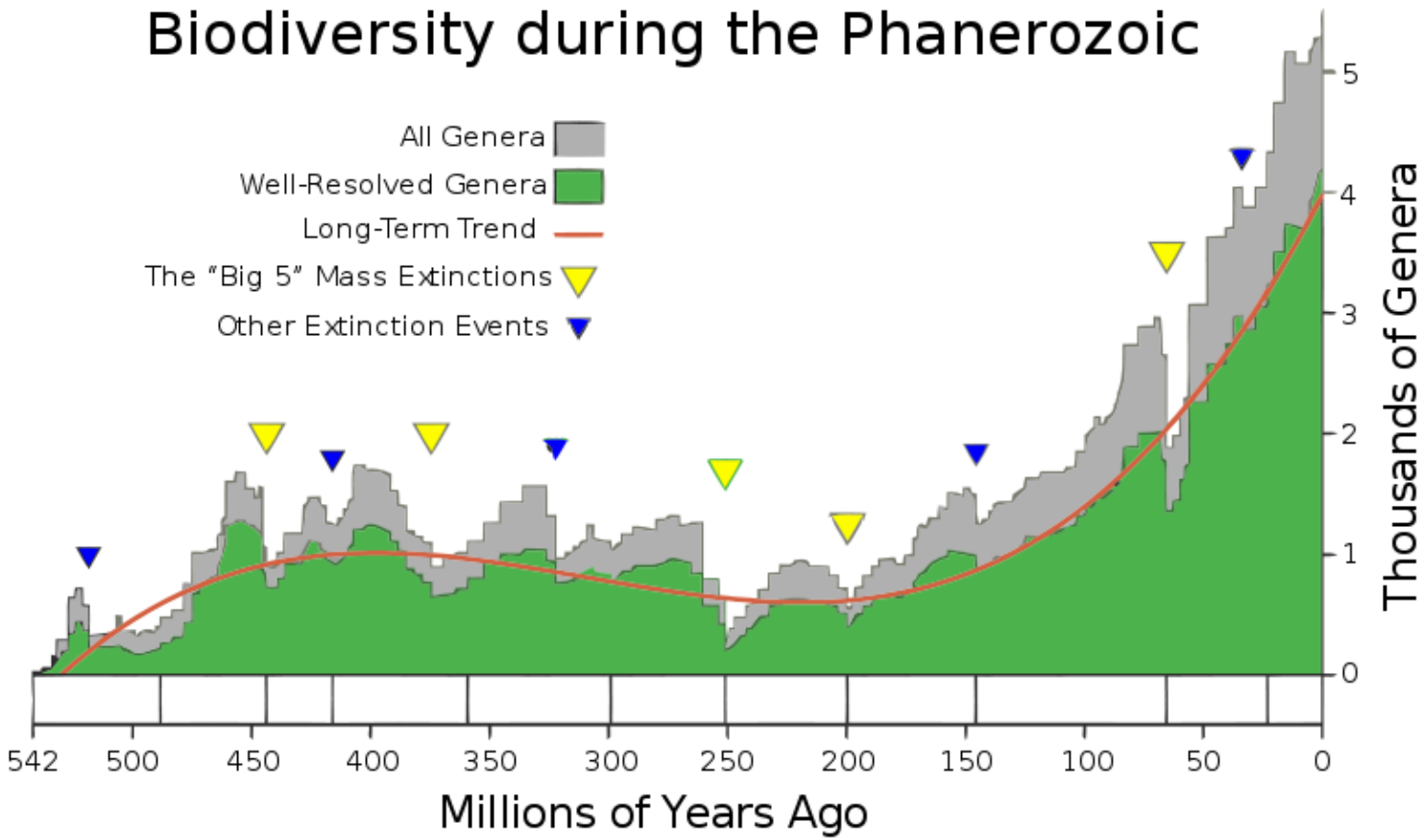
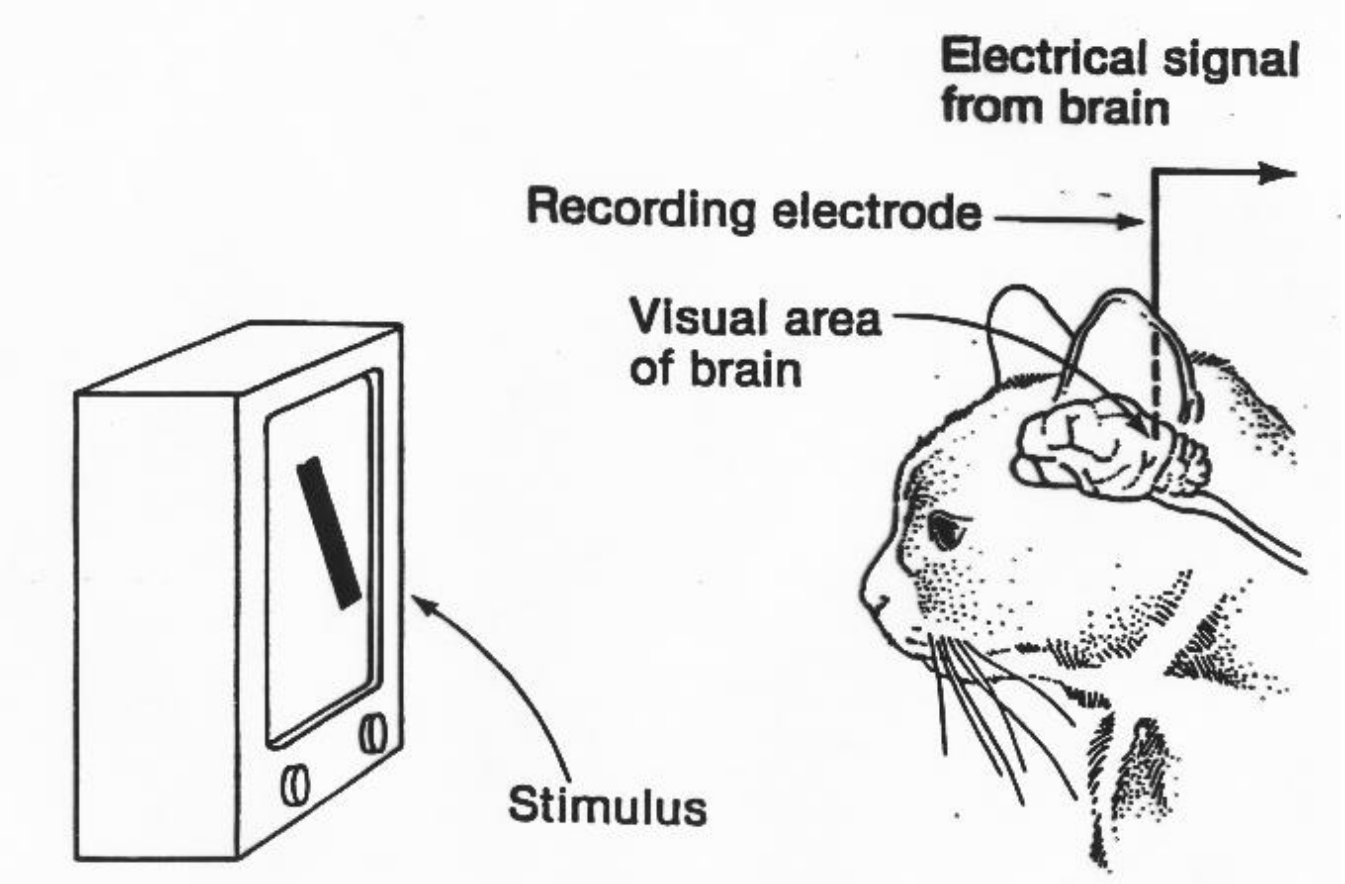
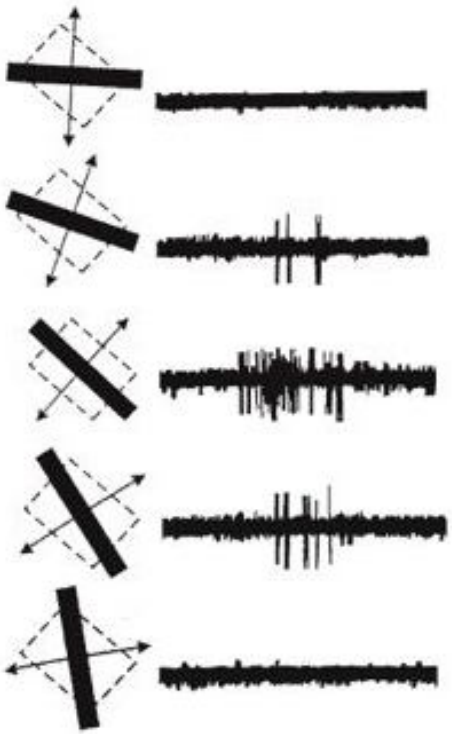
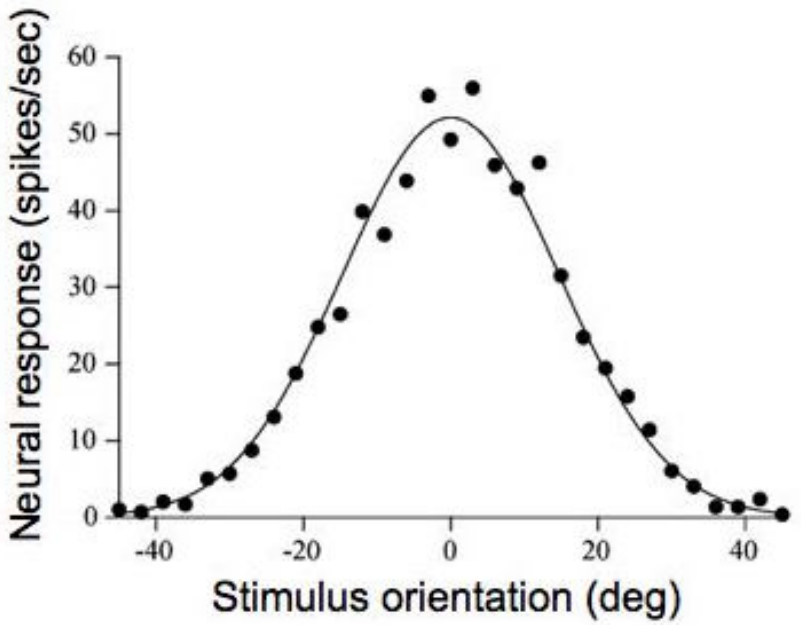




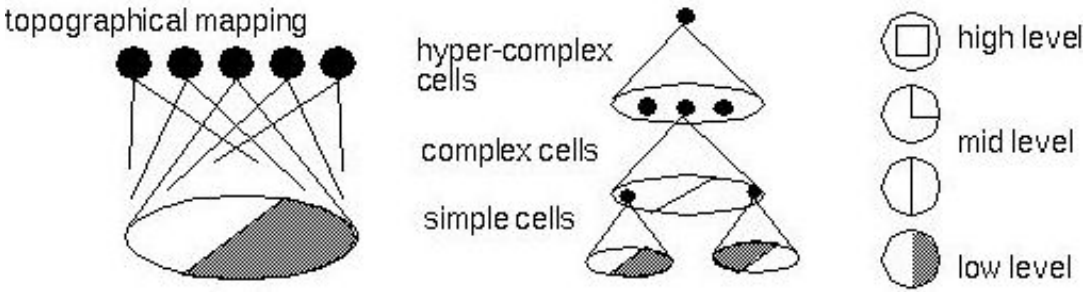
# Hubel & Wiesel (1959)

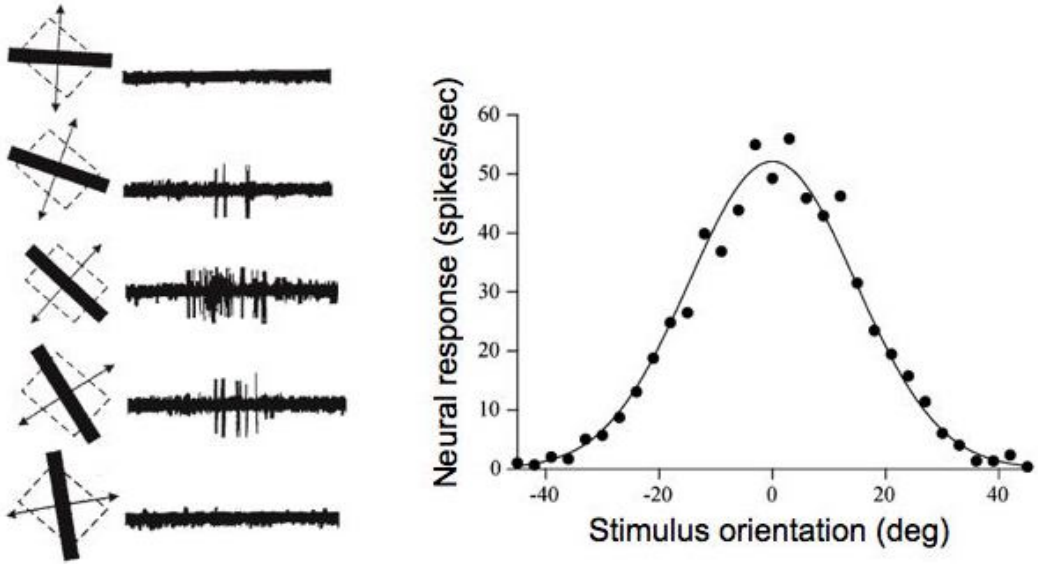







Hubel & Wiesel, 1968

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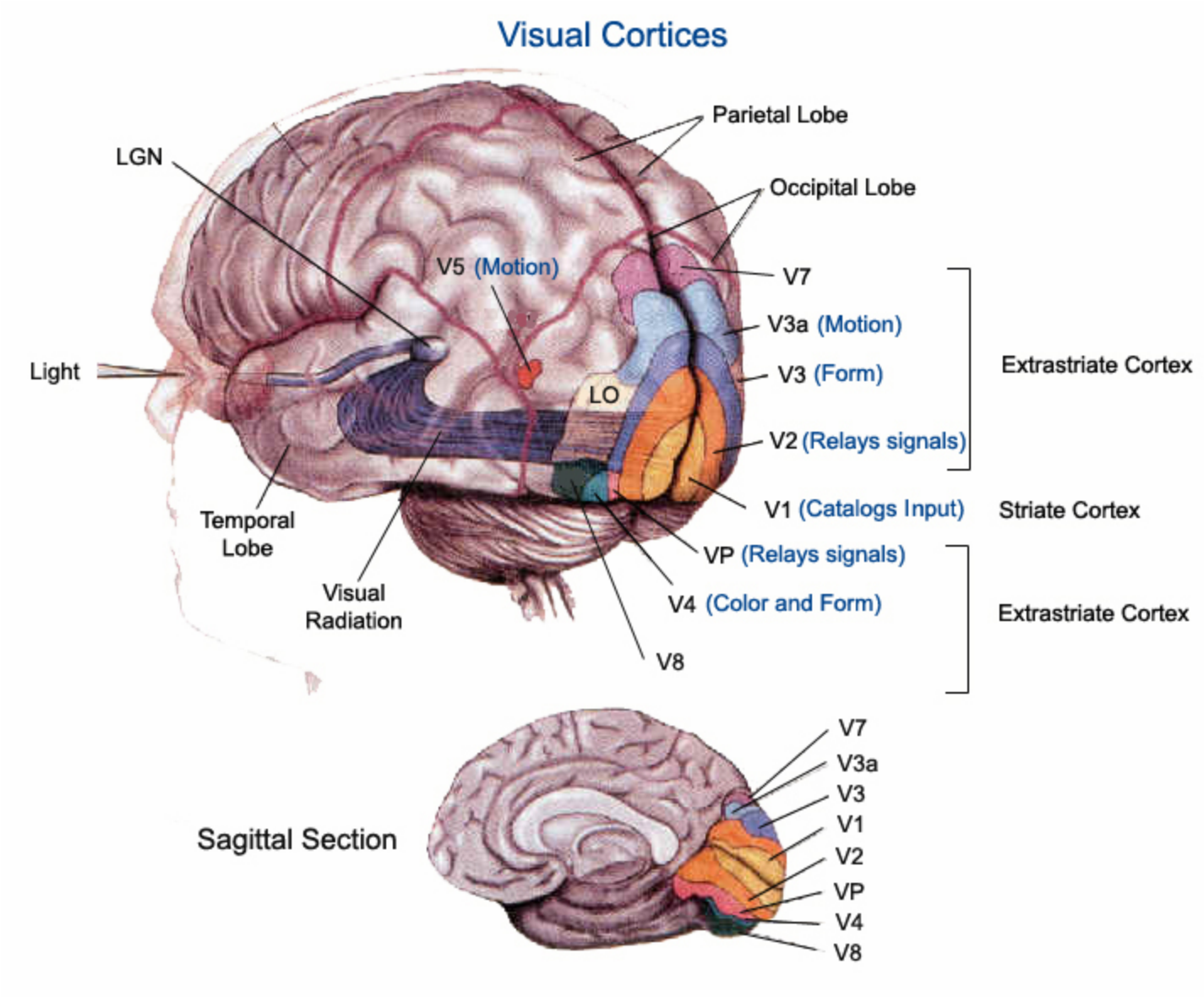
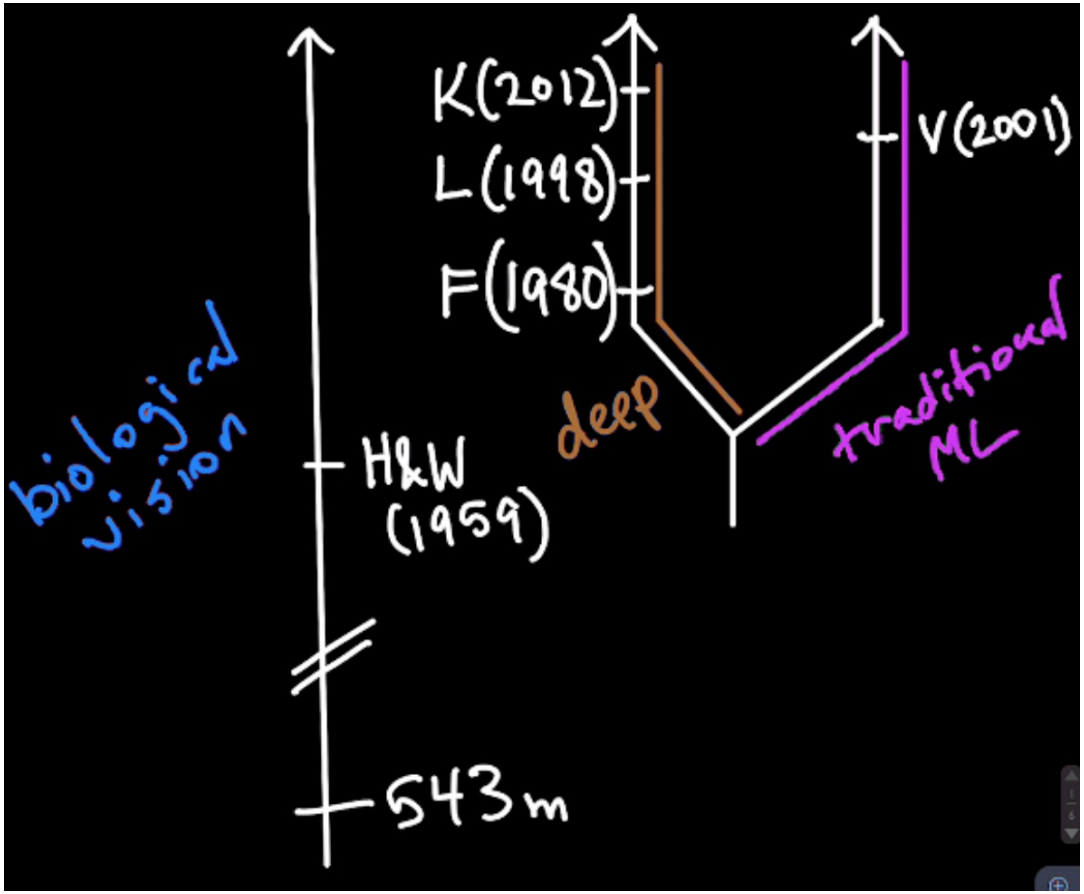
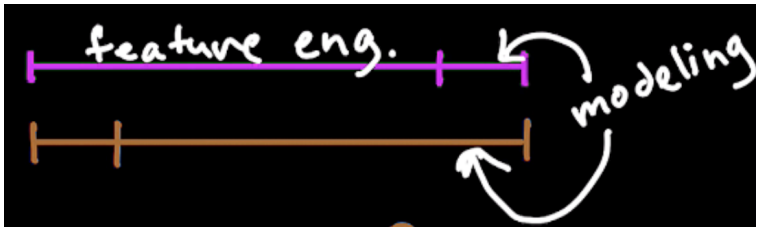
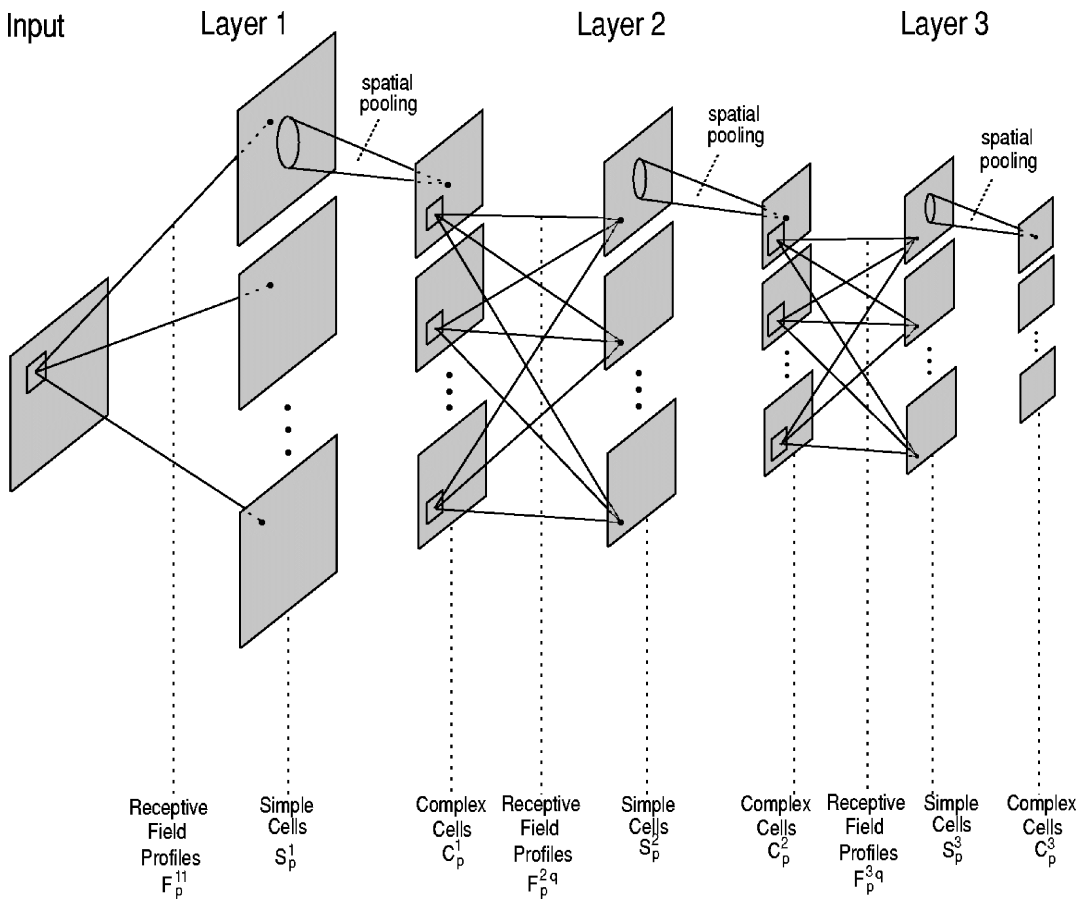


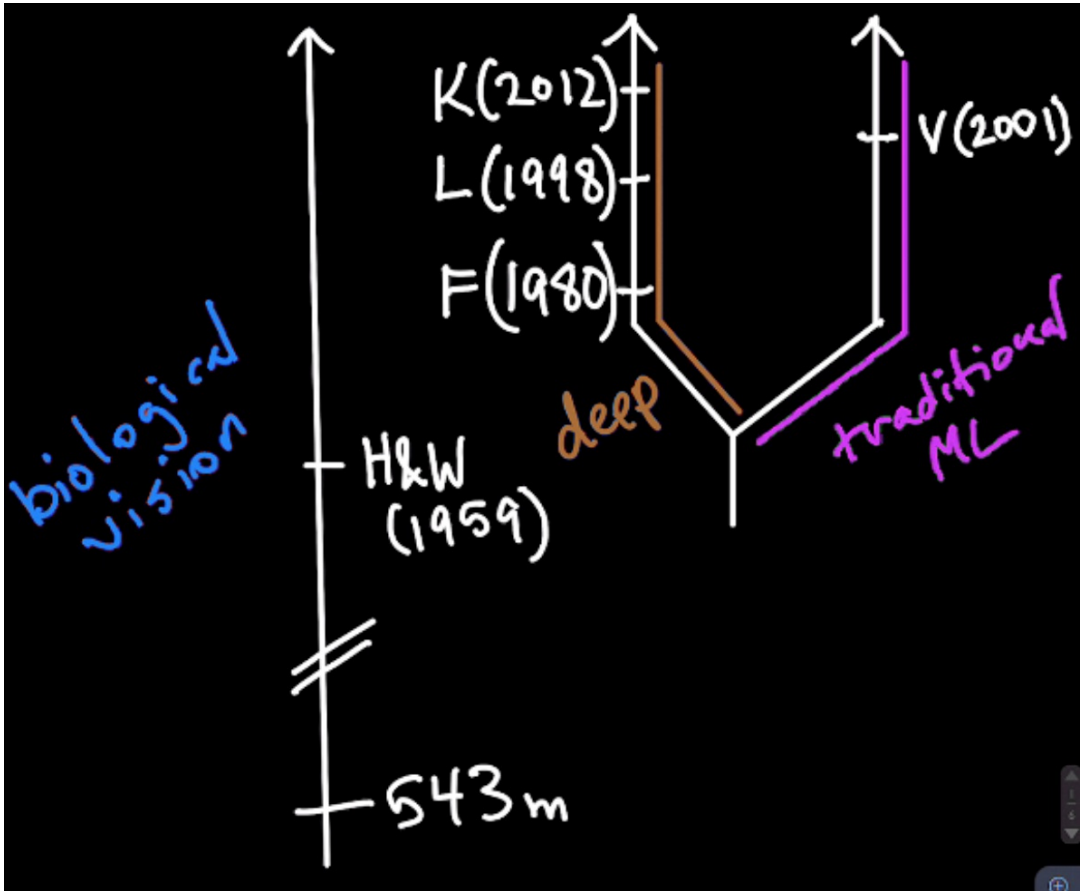


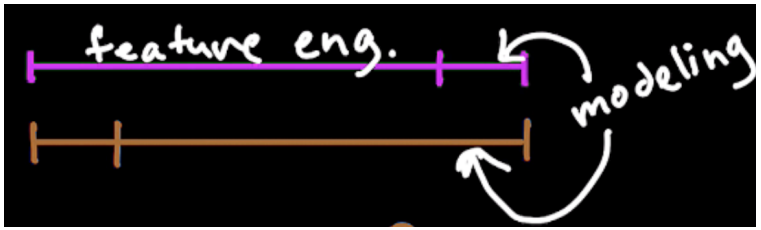



# Neocognitron

## Fukushima (1980)

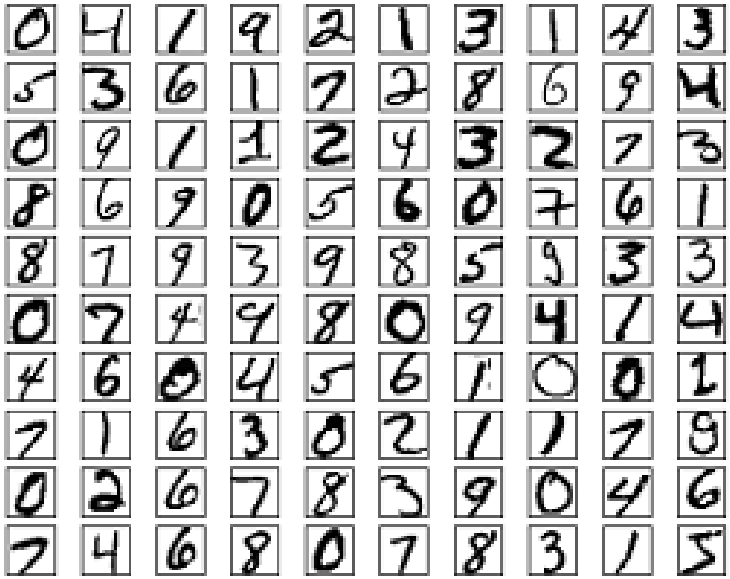




# MNIST Digits & LeNet-5

## LeCun, Boutou, Bengio & Haffner (1998)





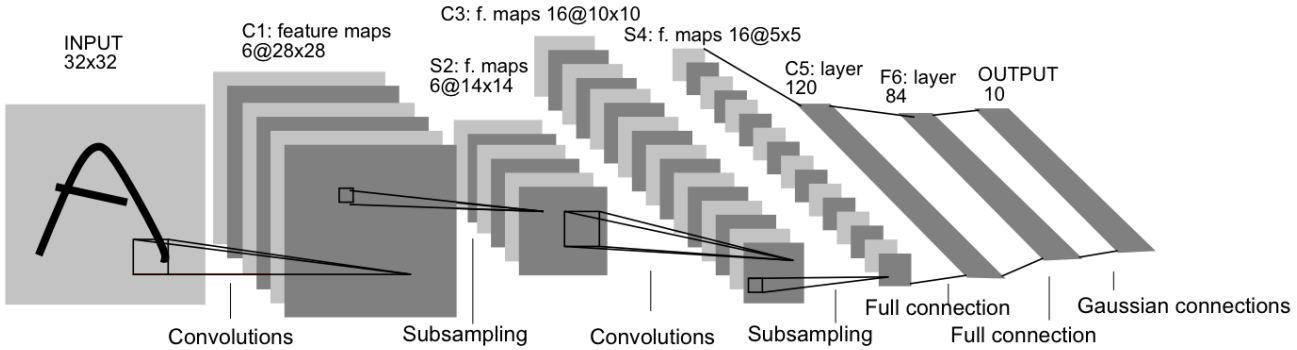
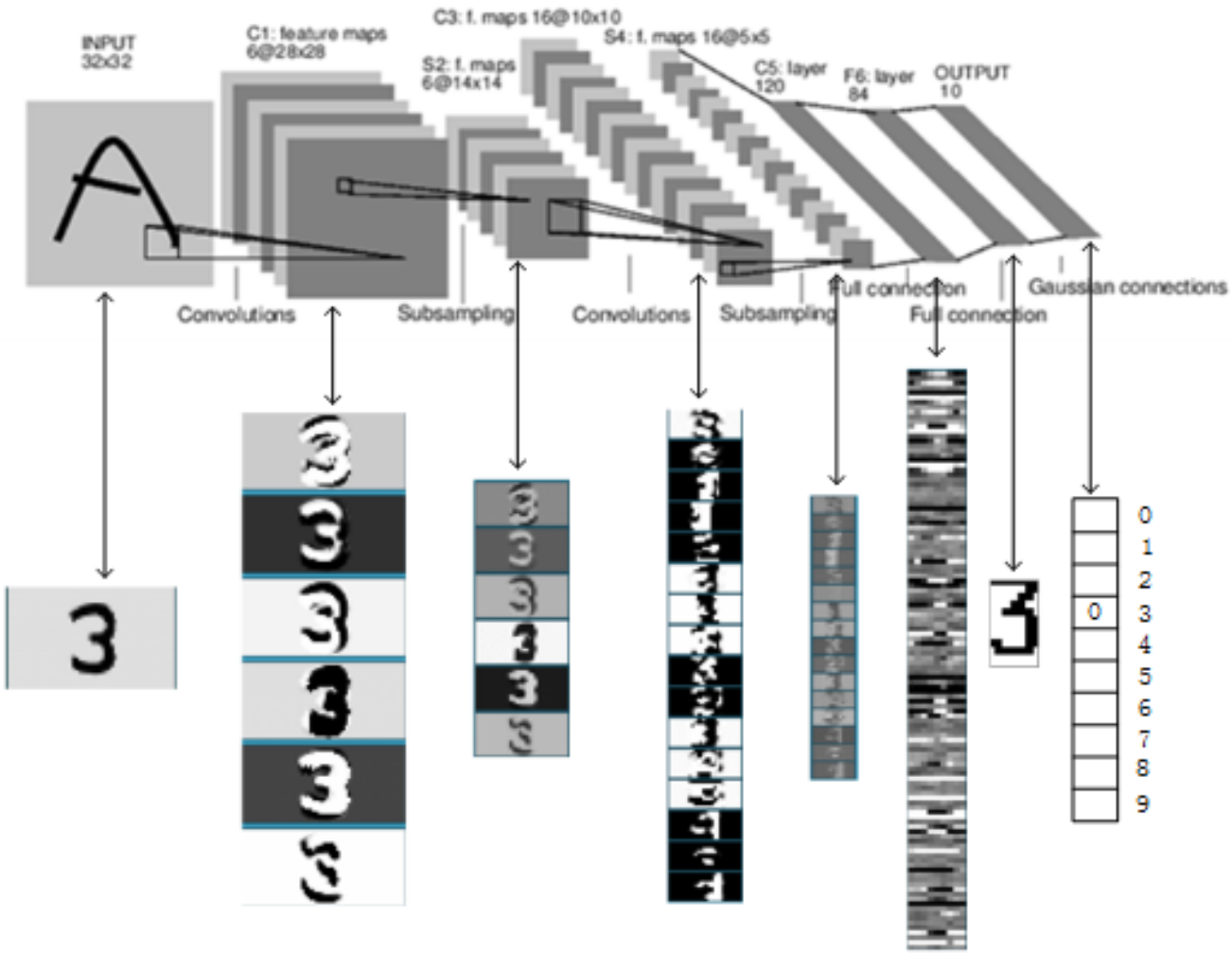
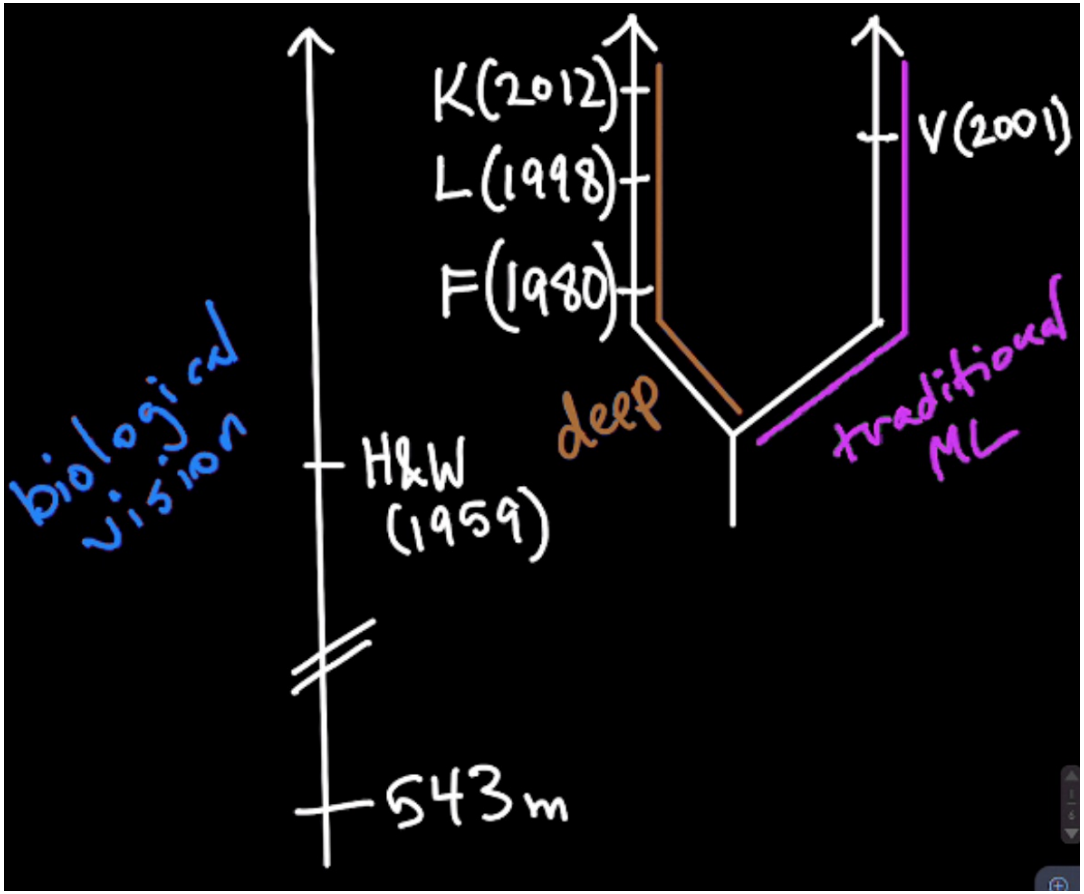


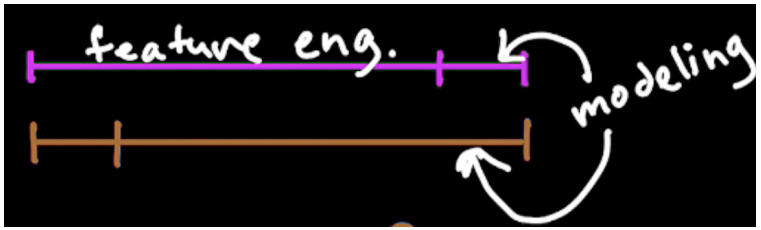

Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

# LeNet-5

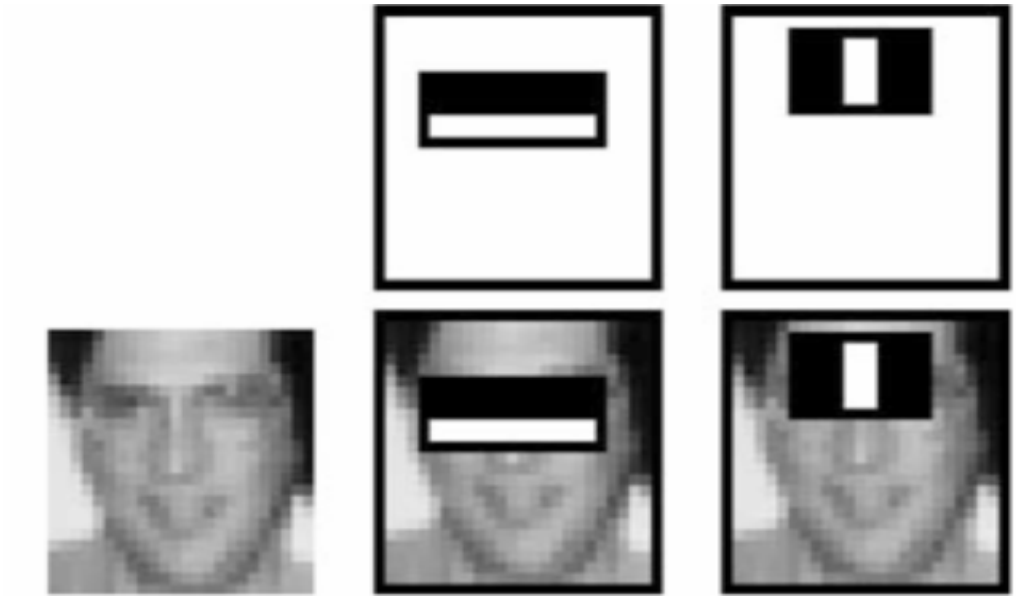
## LeCun, Boutou, Bengio & Haffner (1998)

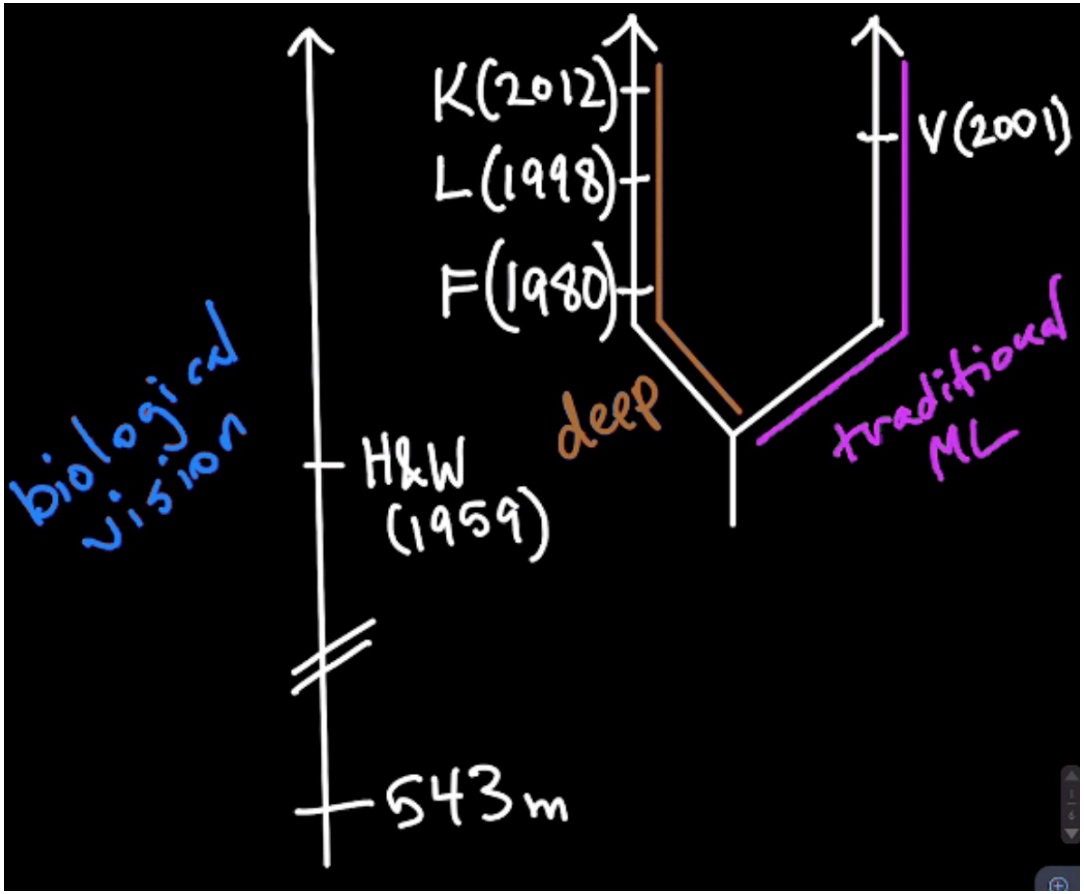


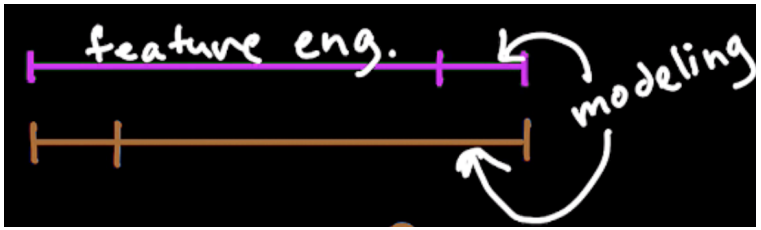


# Viola & Jones (2001)

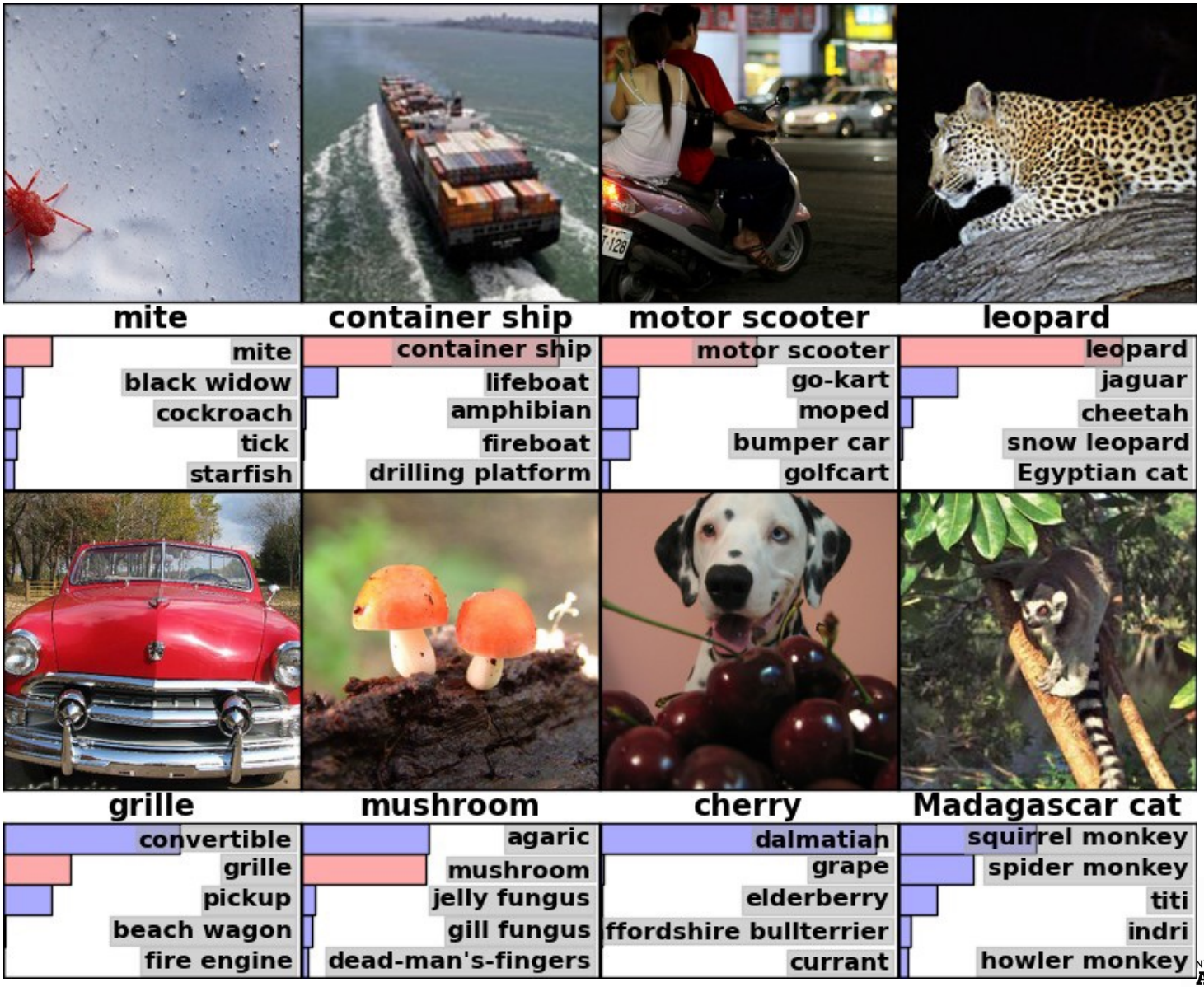




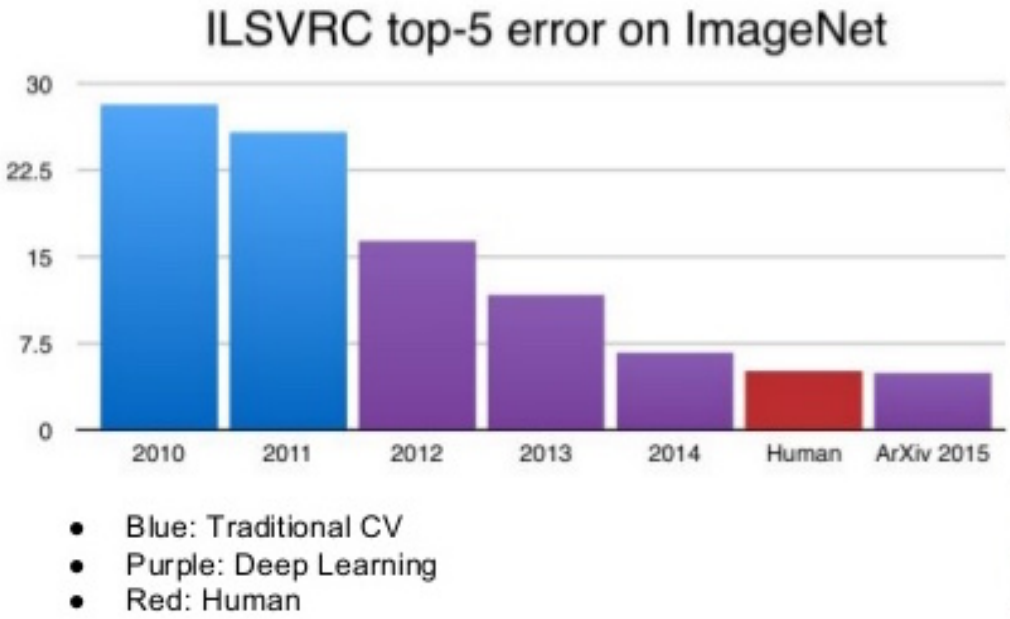
# ImageNet

## Fei-Fei Li et al. (2009), 14m images, 22k categories

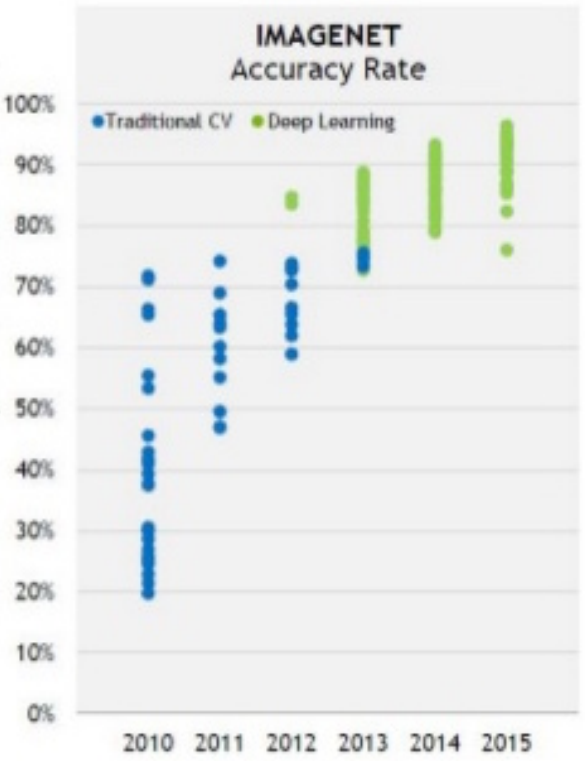


# ImageNet Classification Error

## ILSVRC: 1.4m, 1k object classes

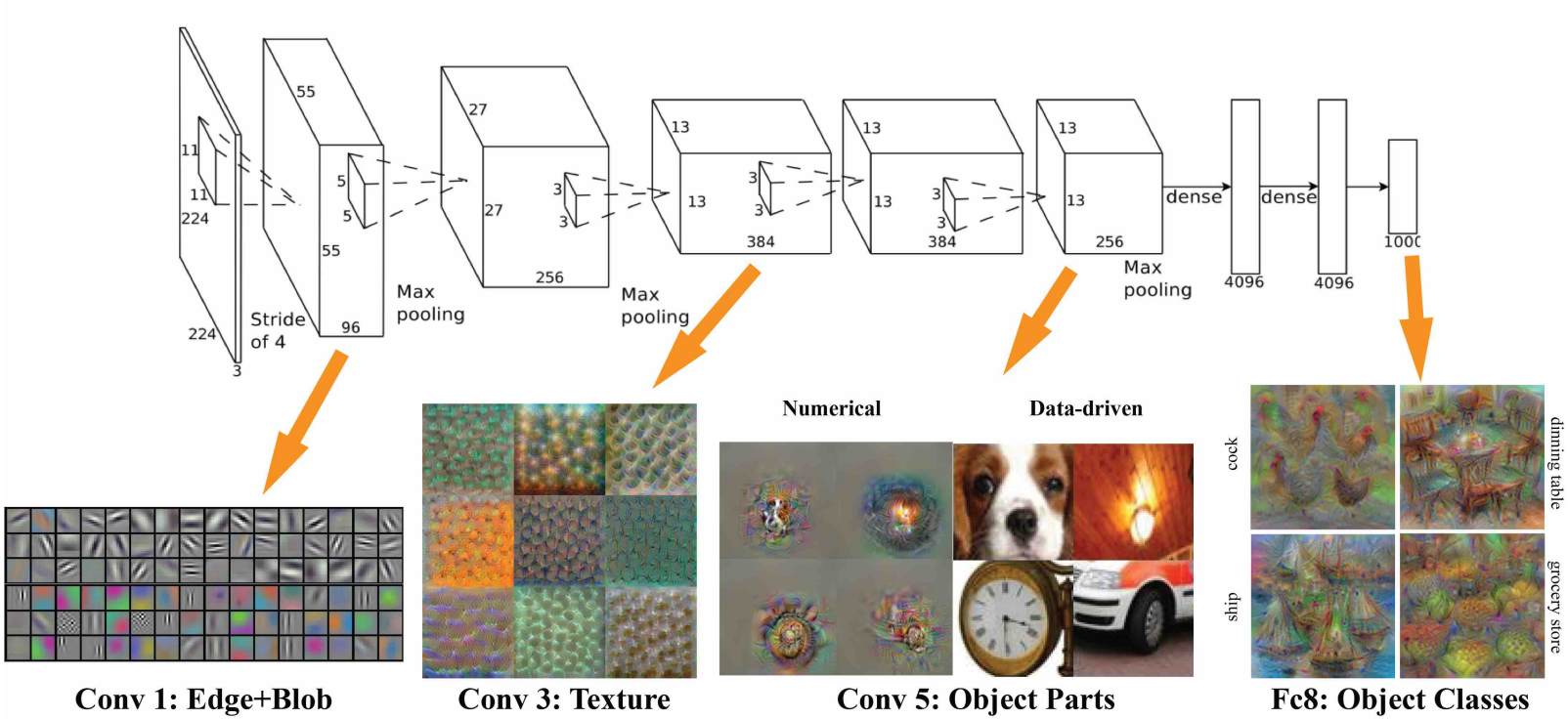


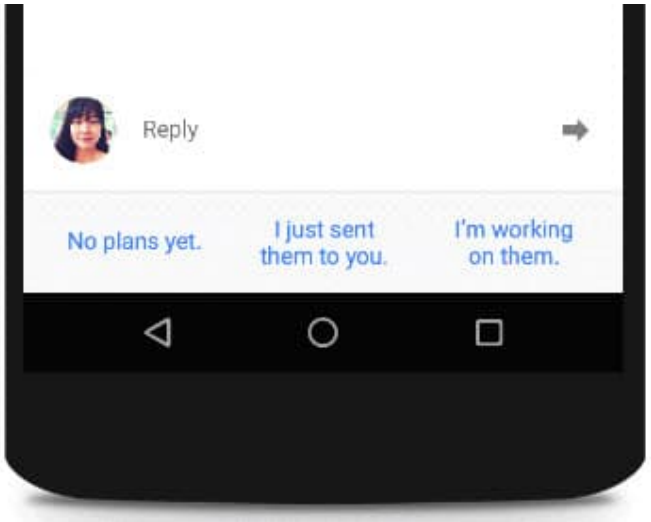

- Blue: Traditional CV
- Purple: Deep Learning
- Red: Human



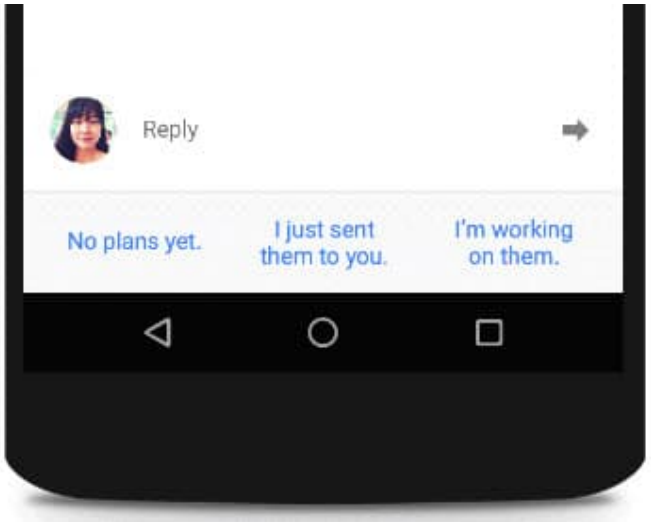
# AlexNet

## Krizhevsky, Sutskever & Hinton (2012)

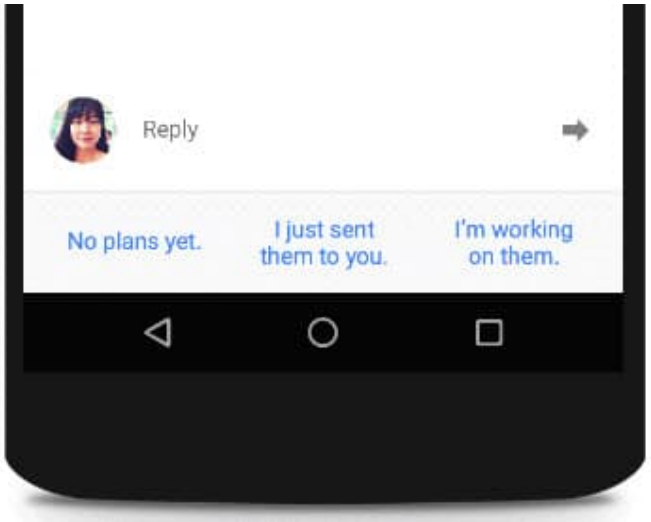


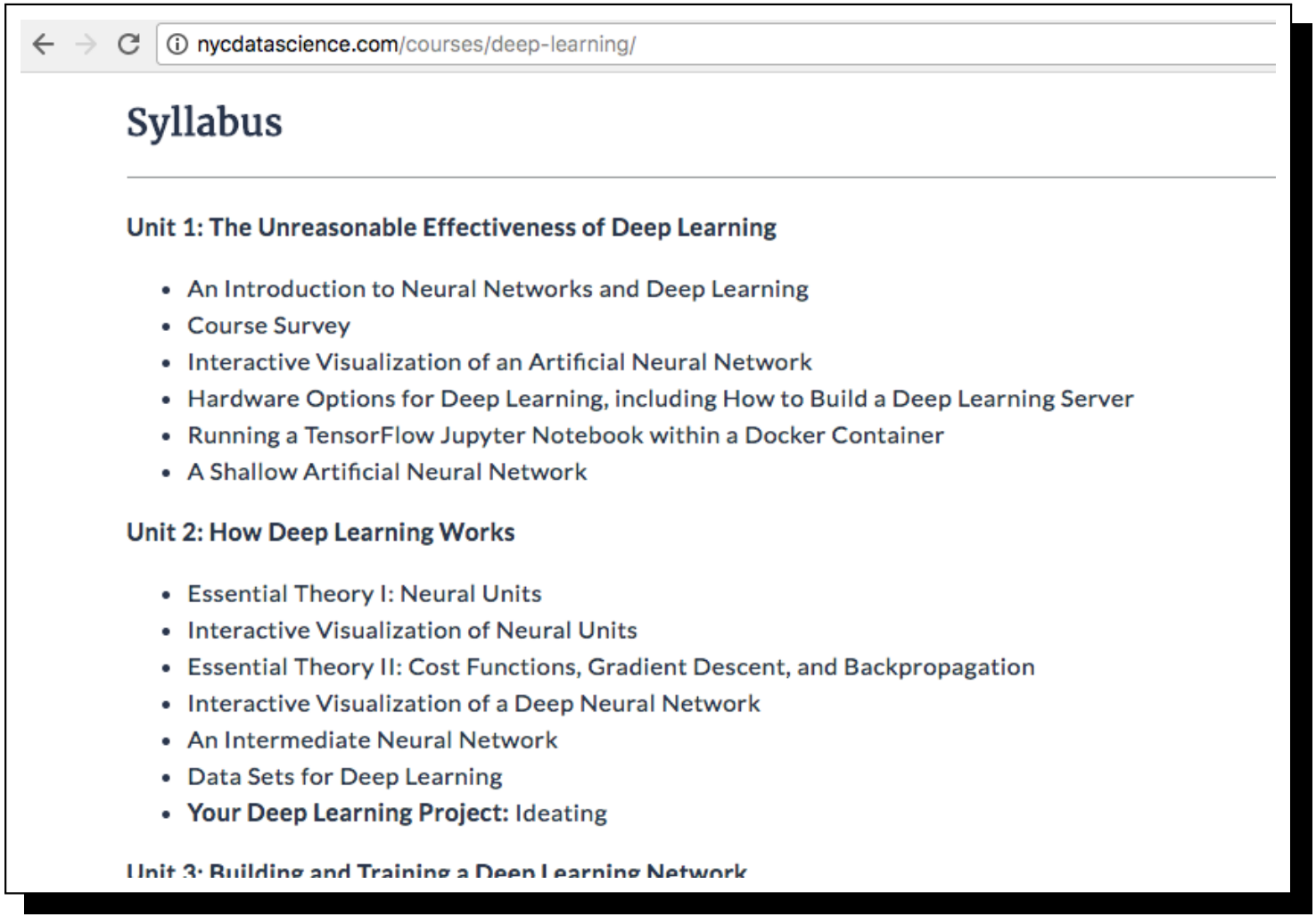








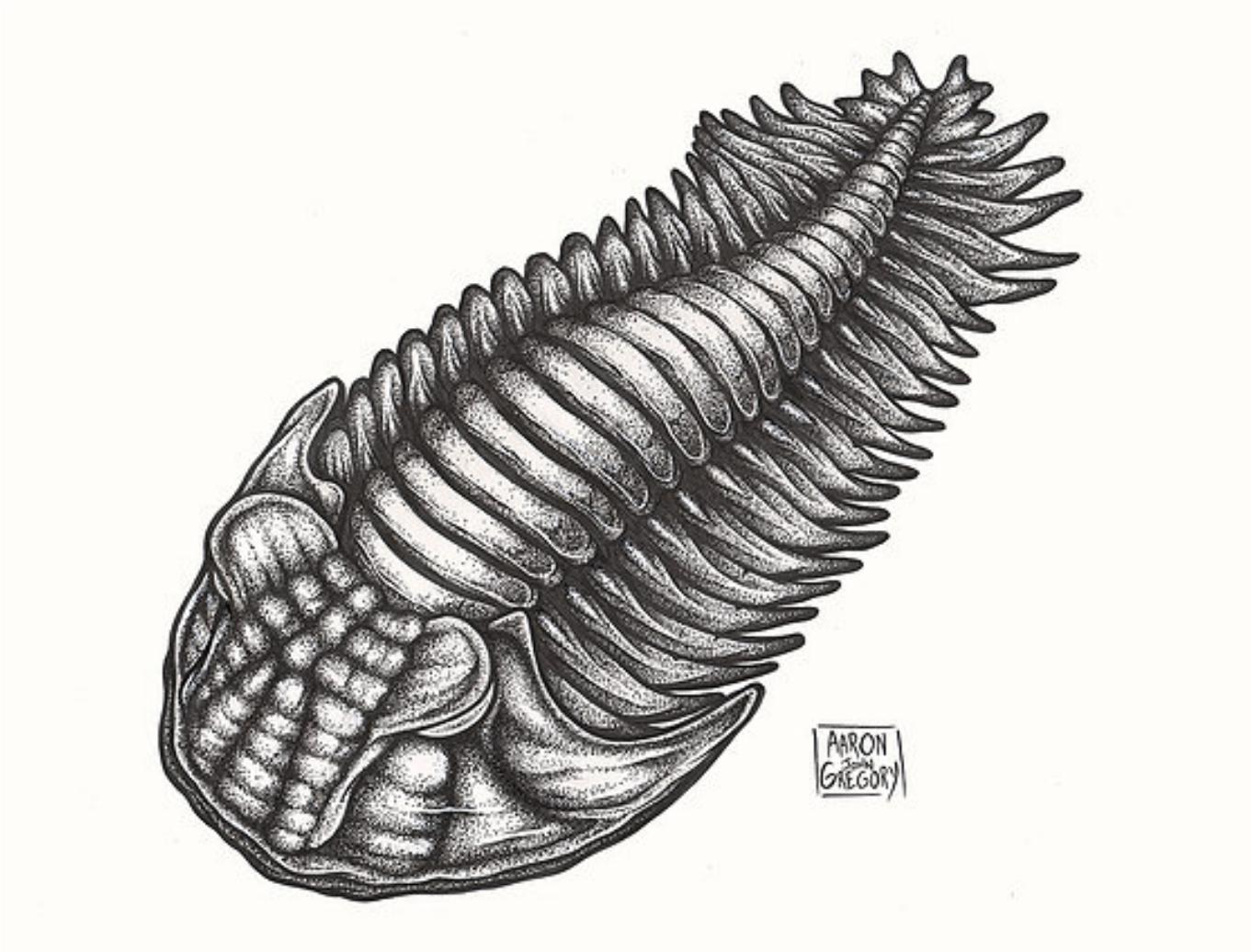

# Outline


nycdatascience.com/courses/deep-learning/
Syllabus
Unit 1: The Unreasonable Effectiveness of Deep Learning
An Introduction to Neural Networks and Deep Learning
Course Survey
Interactive Visualization of an Artificial Neural Network
Hardware Options for Deep Learning, including How to Build a Deep Learning Server
Running a TensorFlow Jupyter Notebook within a Docker Container
A Shallow Artificial Neural Network
Unit 2: How Deep Learning Works
Essential Theory I: Neural Units
Interactive Visualization of Neural Units
Essential Theory II: Cost Functions, Gradient Descent, and Backpropagation
Interactive Visualization of a Deep Neural Network
An Intermediate Neural Network
Data Sets for Deep Learning
Your Deep Learning Project: Ideating
Unit 3: Building and Training a Deep Learning Network

# Outline

# The Unreasonable Effectiveness of Deep Learning

## Unit 1: right now!

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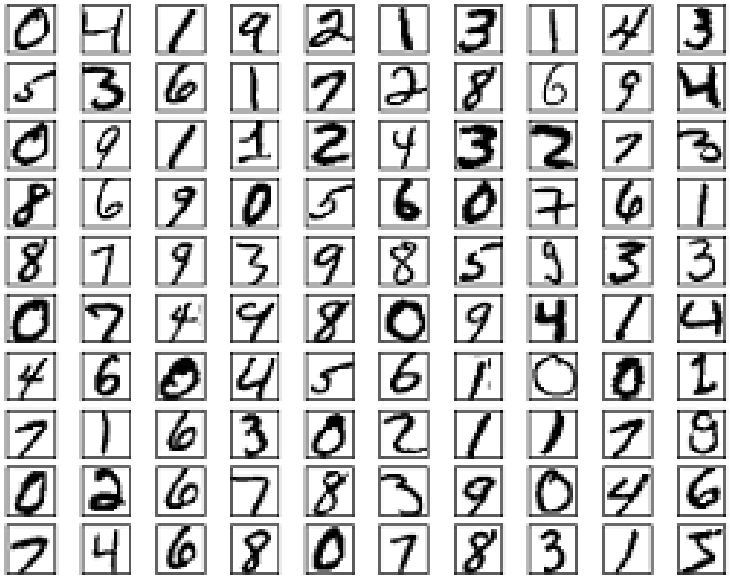
# Hardware Options for DL

# Jupyter Notebooks

## + Docker + Nvidia GPU + TensorFlow

# A Shallow Neural Network

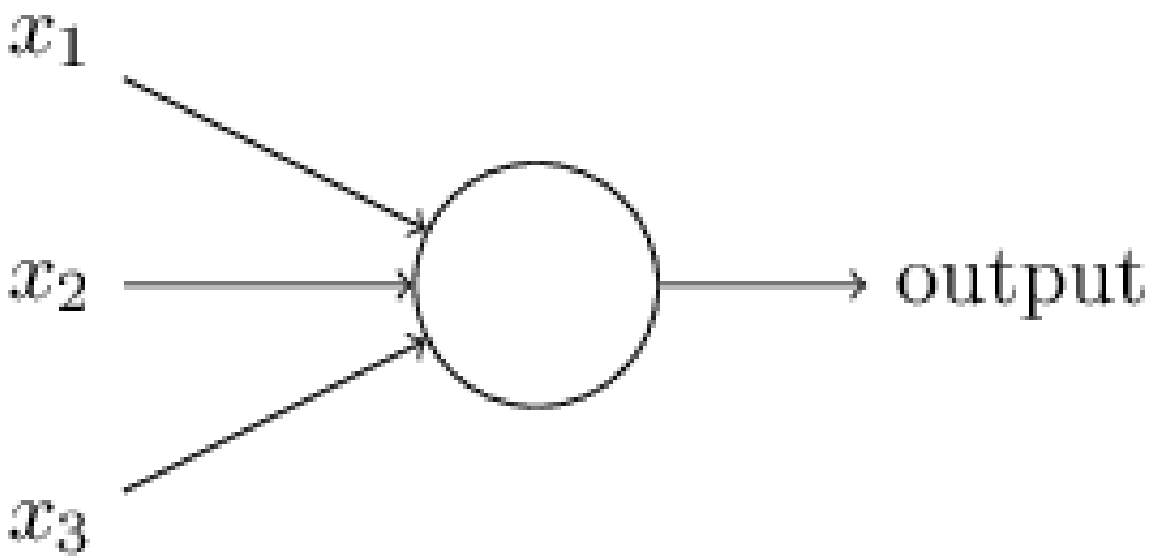


# How Deep Learning Works

## Unit 2: This Afternoon

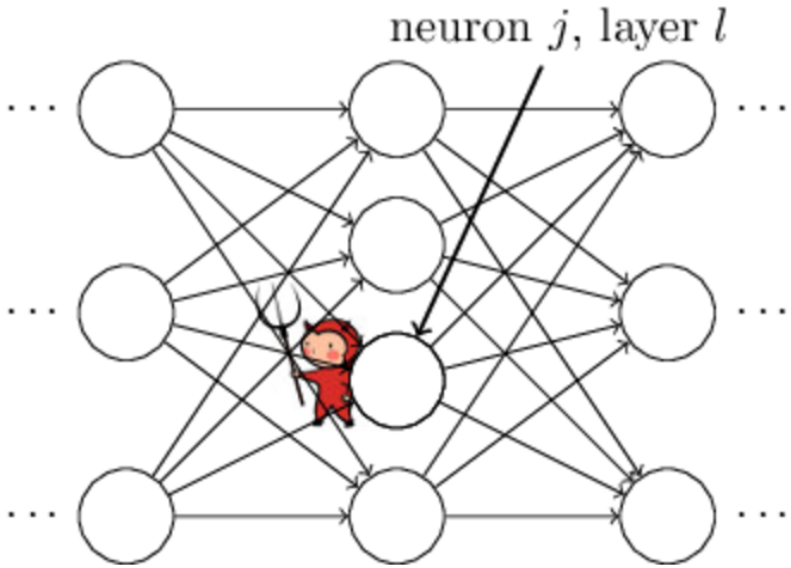
# Essential Theory I

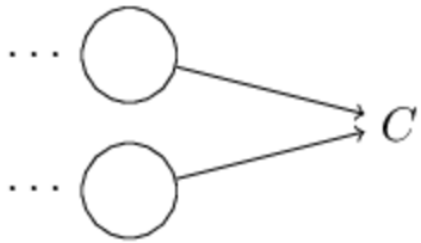
## Neural Units



# Essential Theory II

## Cost Functions, Gradient Descent, and Backpropagation

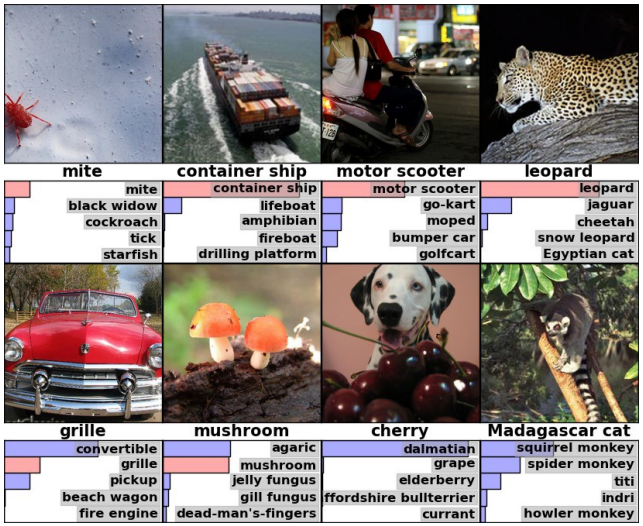


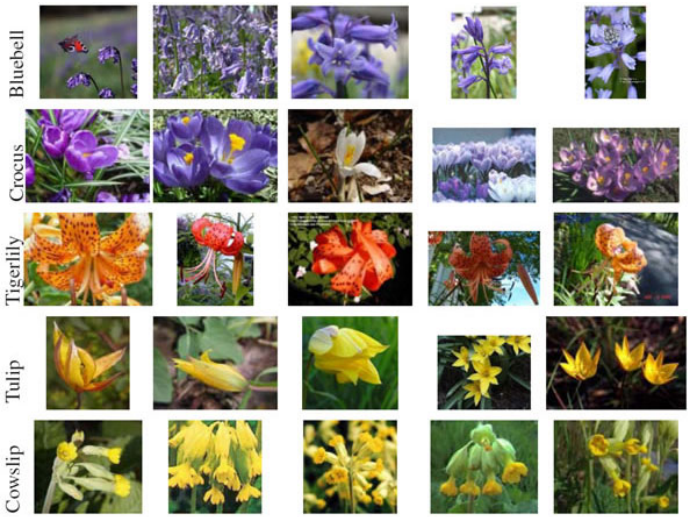



# An Intermediate Neural Network

[intermediate notebook]

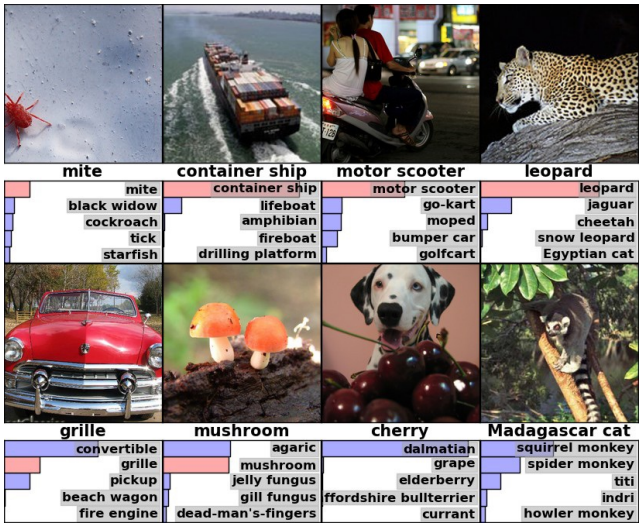
# Data Sets for Deep Learning

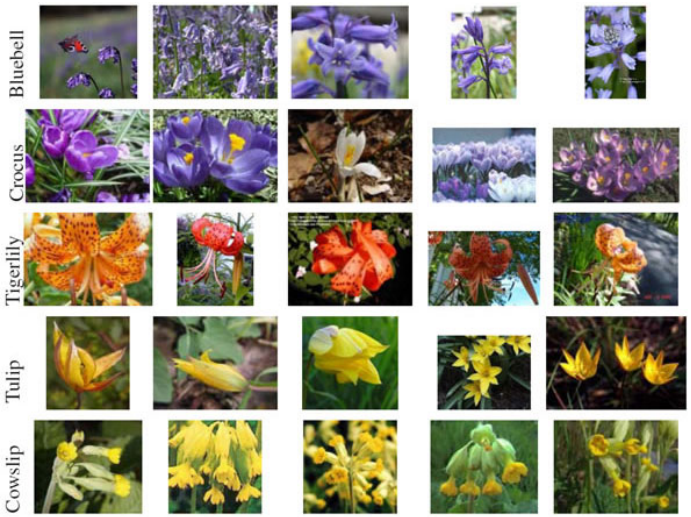



| Dataset | Classes | Train Samples |
|---|---|---|
| AG's News | 4 | 120,000 |
| Sogou News | 5 | 450,000 |
| DBPedia | 14 | 560,000 |
| Yelp Review Polarity | 2 | 560,000 |
| Yelp Review Full | 5 | 650,000 |
| Yahoo! Answers | 10 | 1,400,000 |
| Amazon Review Full | 5 | 3,000,000 |
| Amazon Review Polarity | 2 | 3,600,000 |

# Data Sets for Deep Learning

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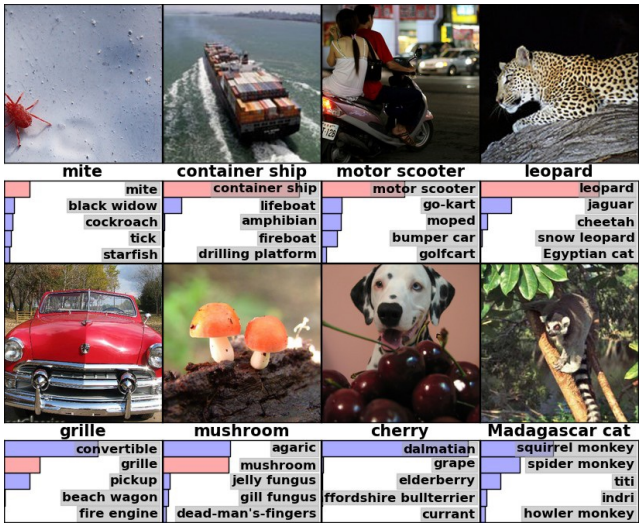


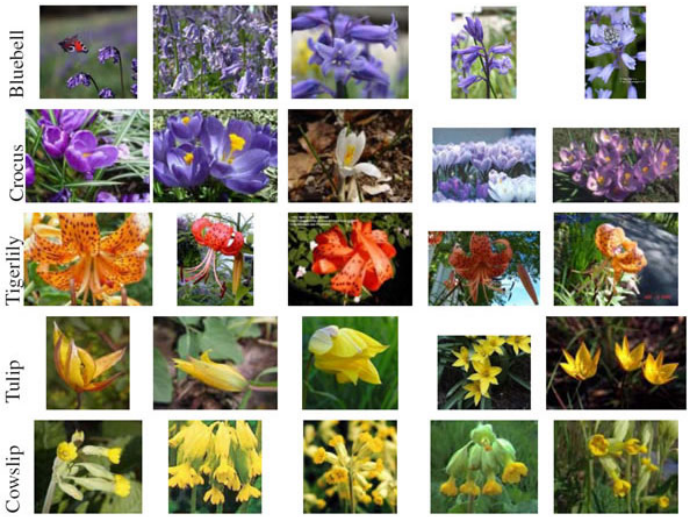


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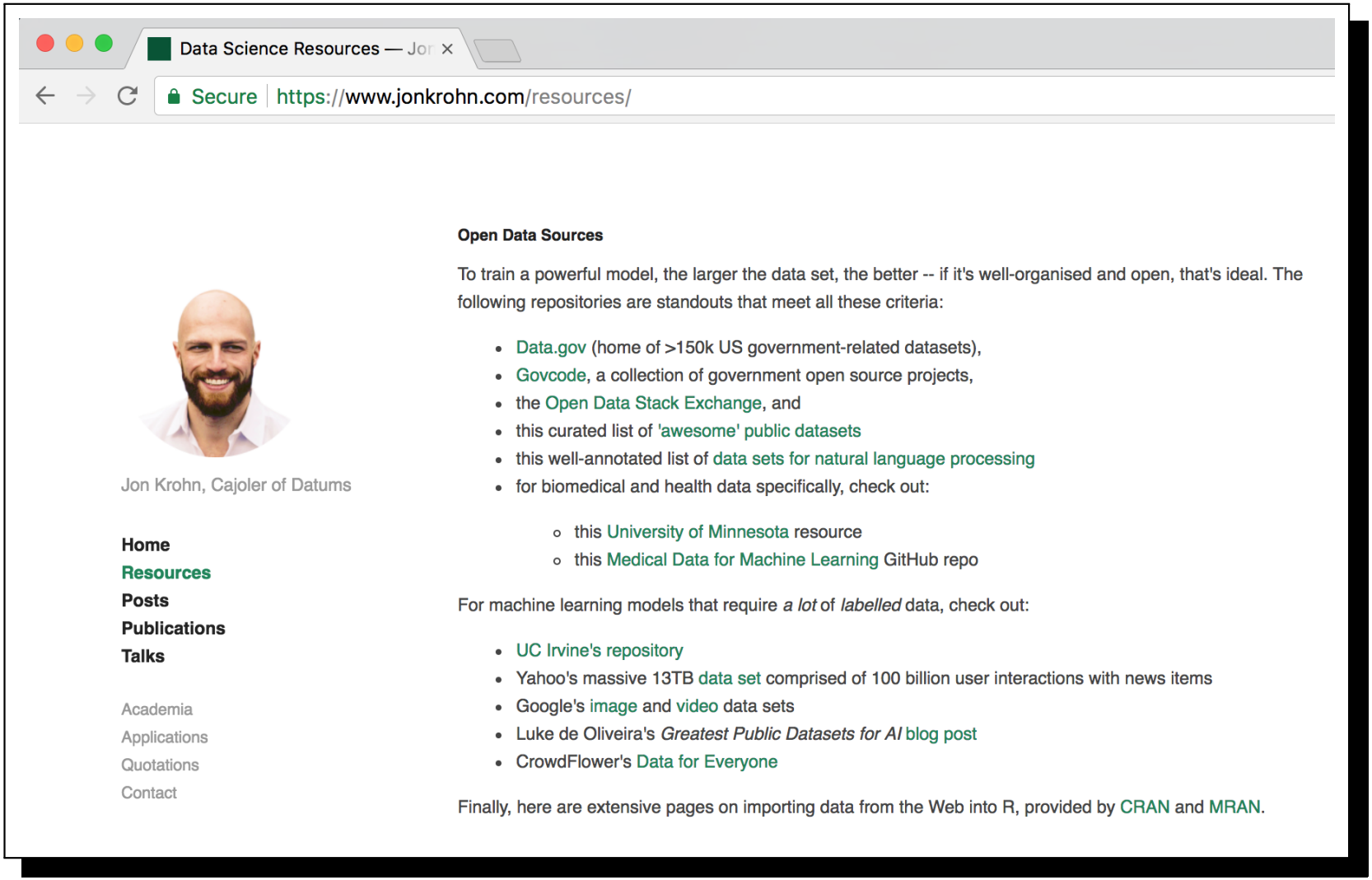
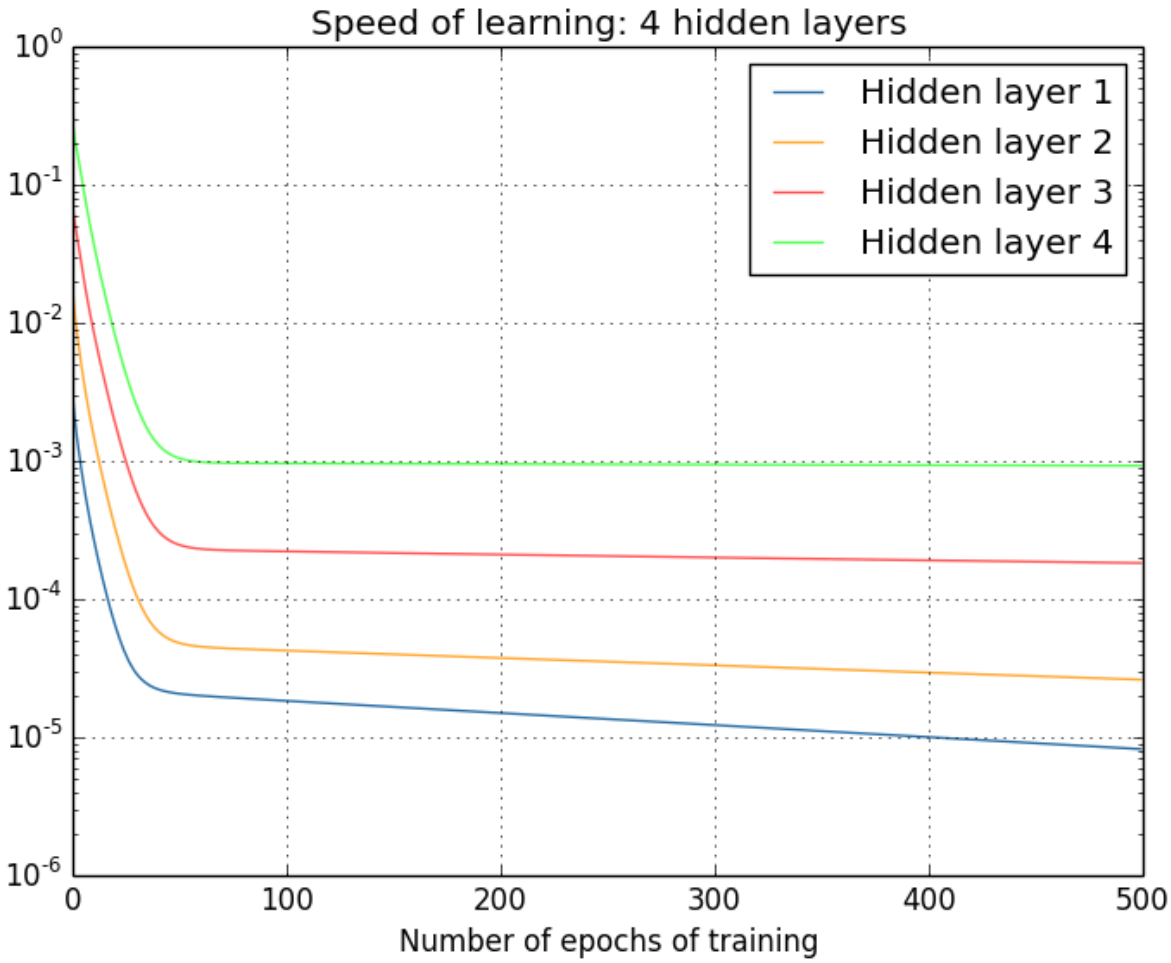


# Your Deep Learning Project I

## Ideating

# Building & Training a Deep Network

## Unit 3: March 10th AM



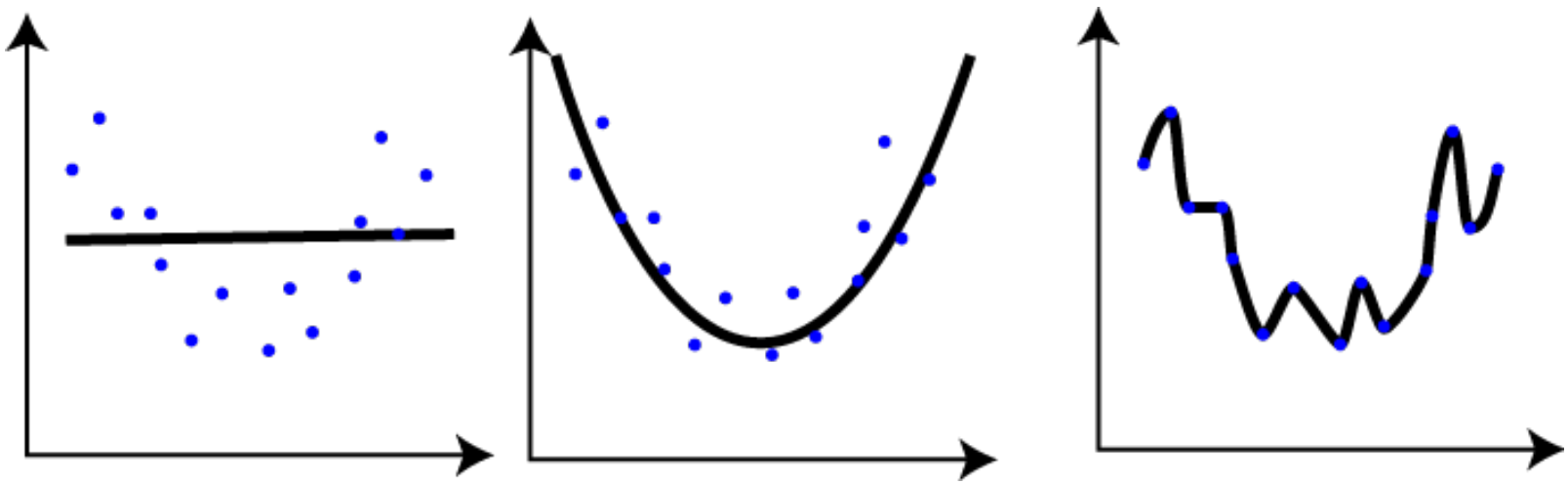
# Essential Theory III

## Weight Initialization and Mini-Batches

[neurons notebook]

# Essential Theory IV

## Unstable Gradients and Avoiding Overfitting

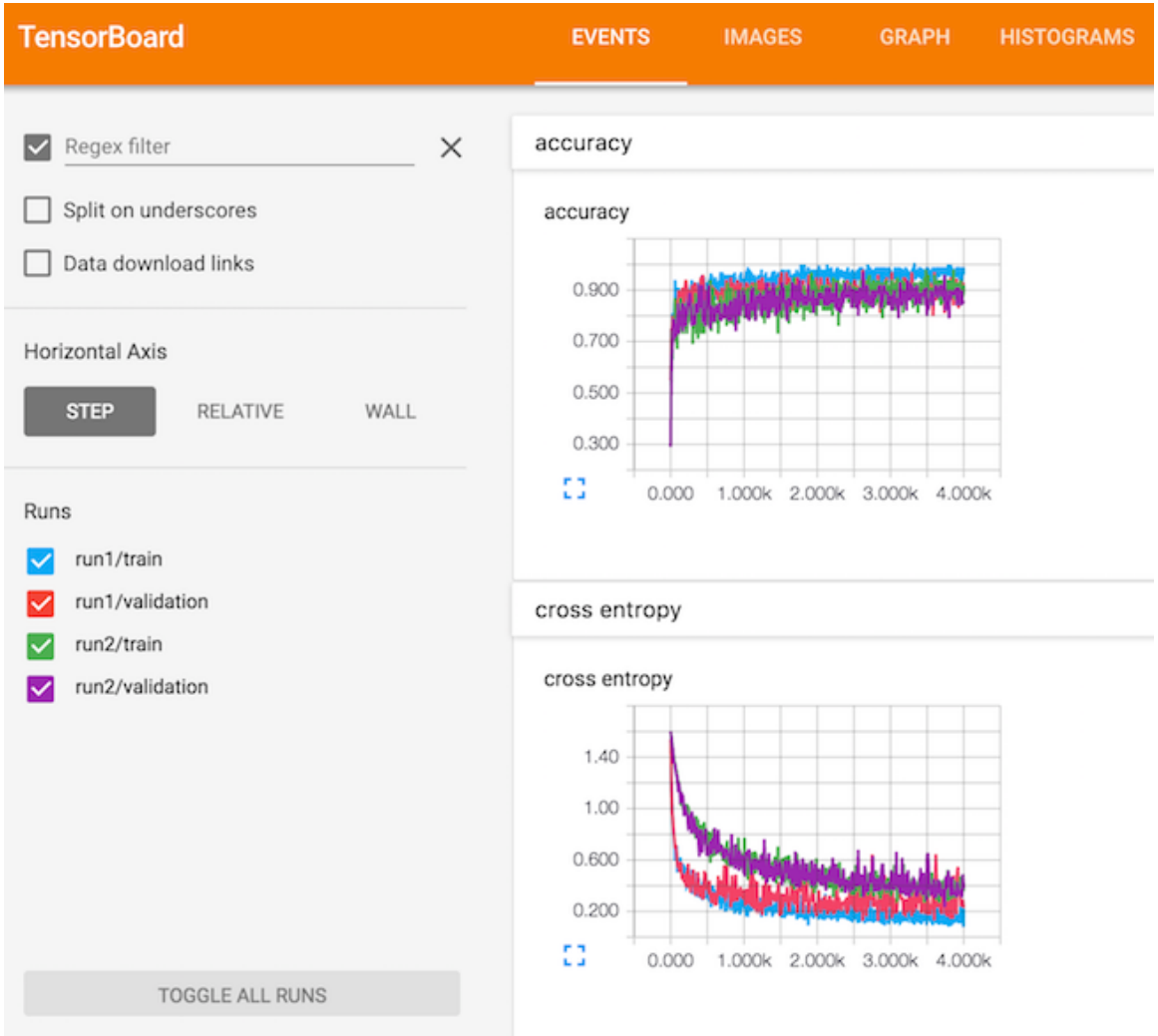


# A Deep Neural Network

[deep notebook]

# TensorBoard

## and the Interpretation of Model Outputs

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# Outline

# Machine Vision

## Unit 4: March 10th PM

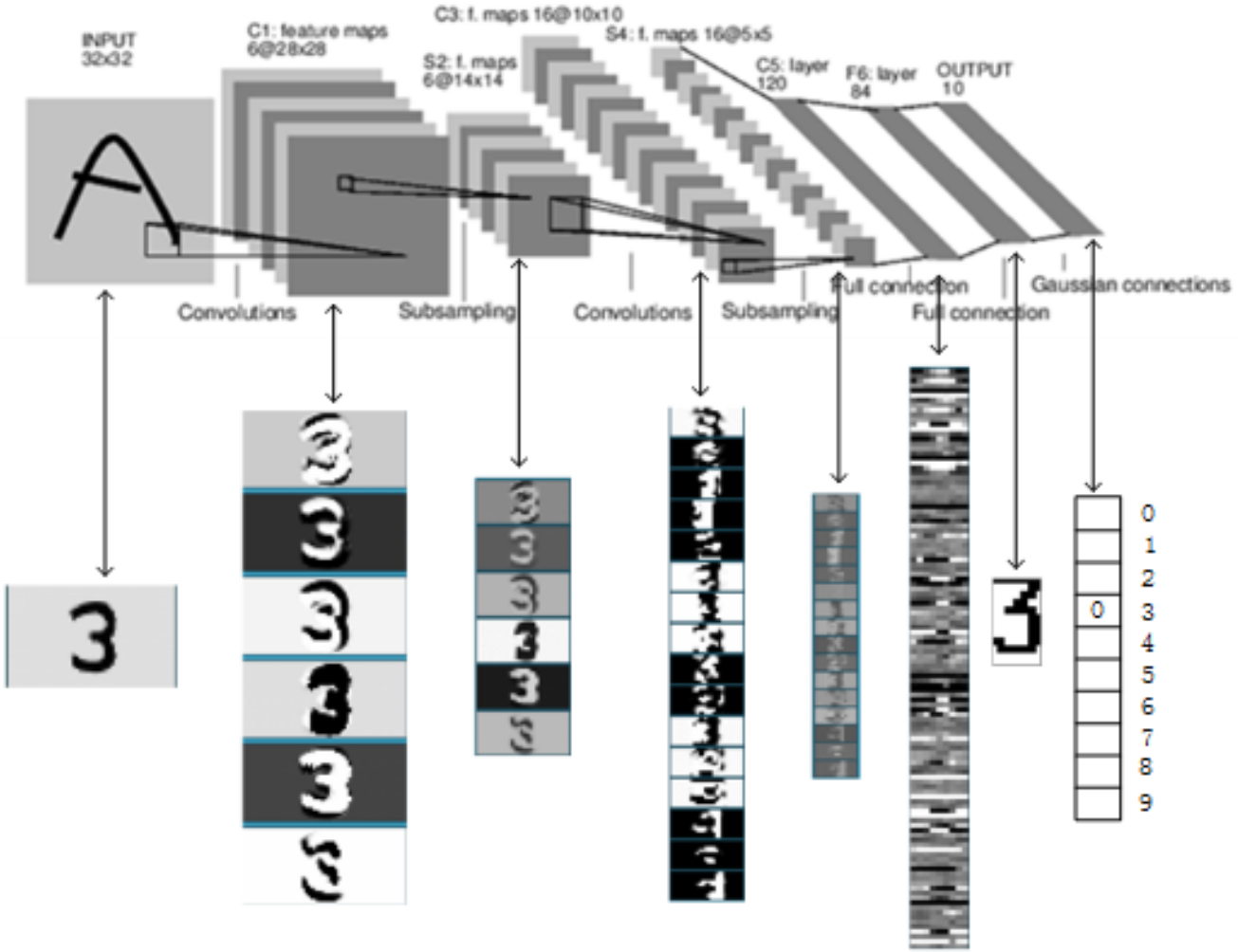
# Intro to ConvNets

## for Visual Recognition

[deepvis]

# LeNet-5

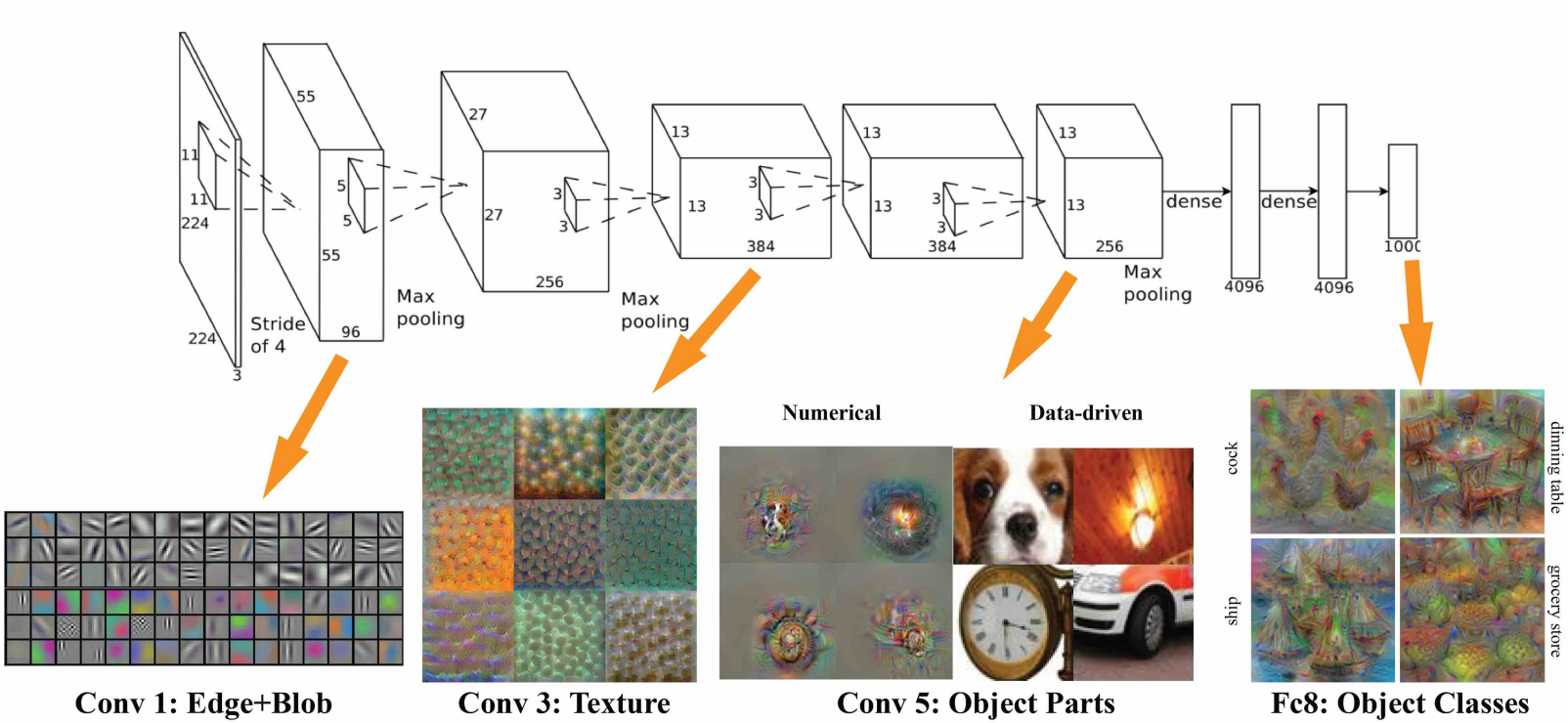
## Classic ConvNet Architecture I




[notebook]

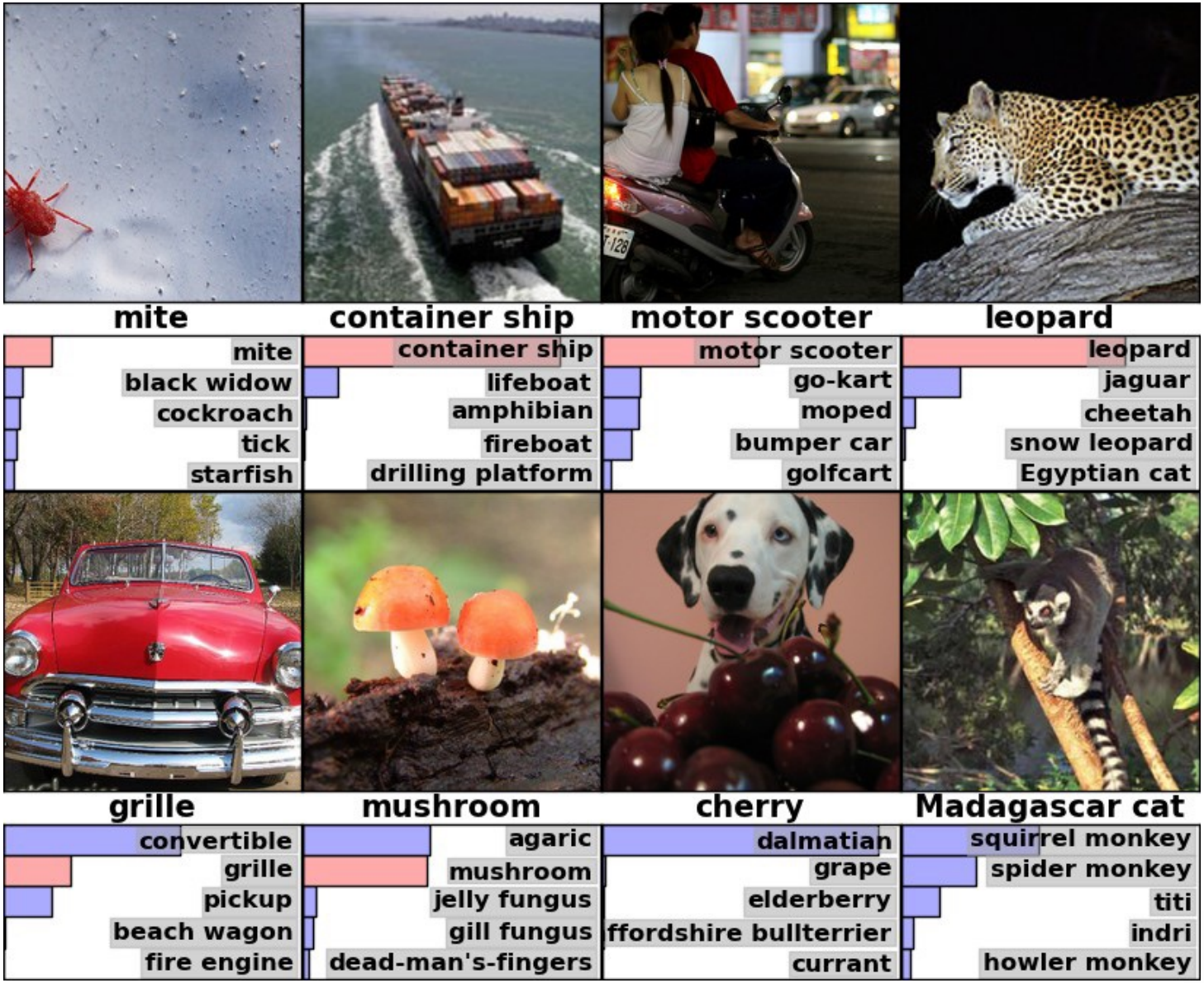
# AlexNet

## Classic ConvNet Architecture II




[notebook]

# Transfer Learning

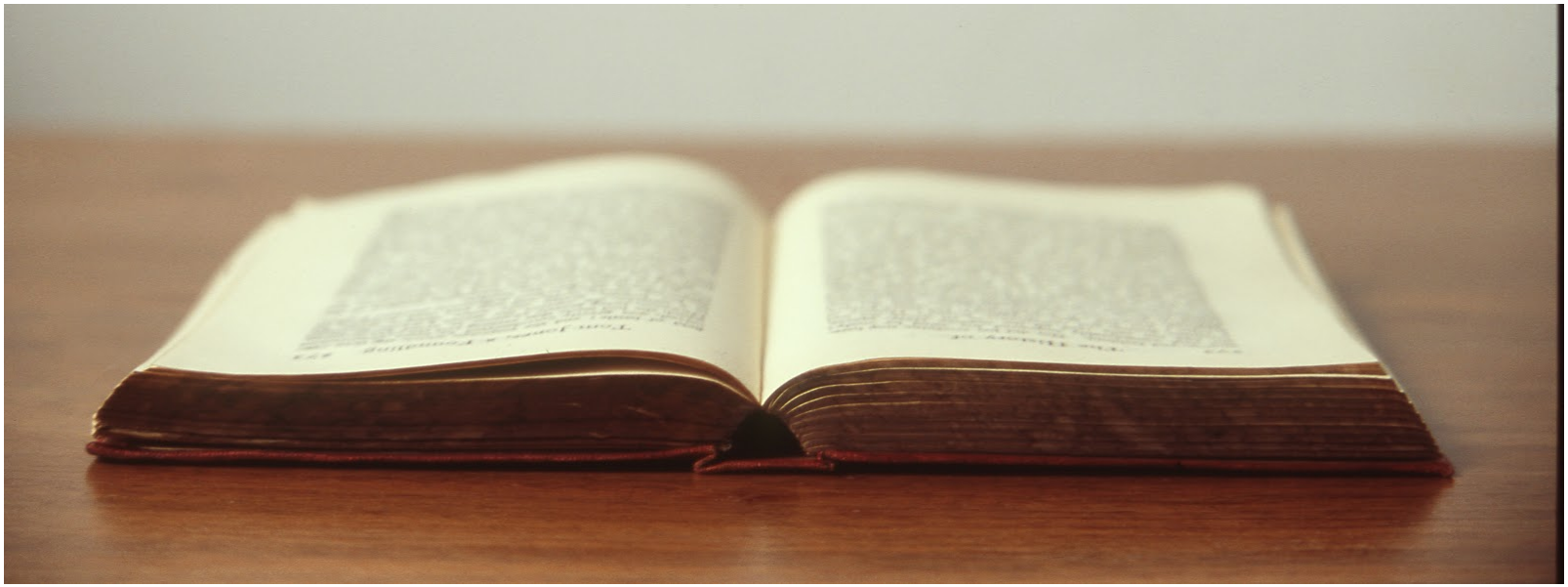


# Your Deep Learning Project II

## Formulating

# Natural Language Processing

## Units 5 & 6: March 17th



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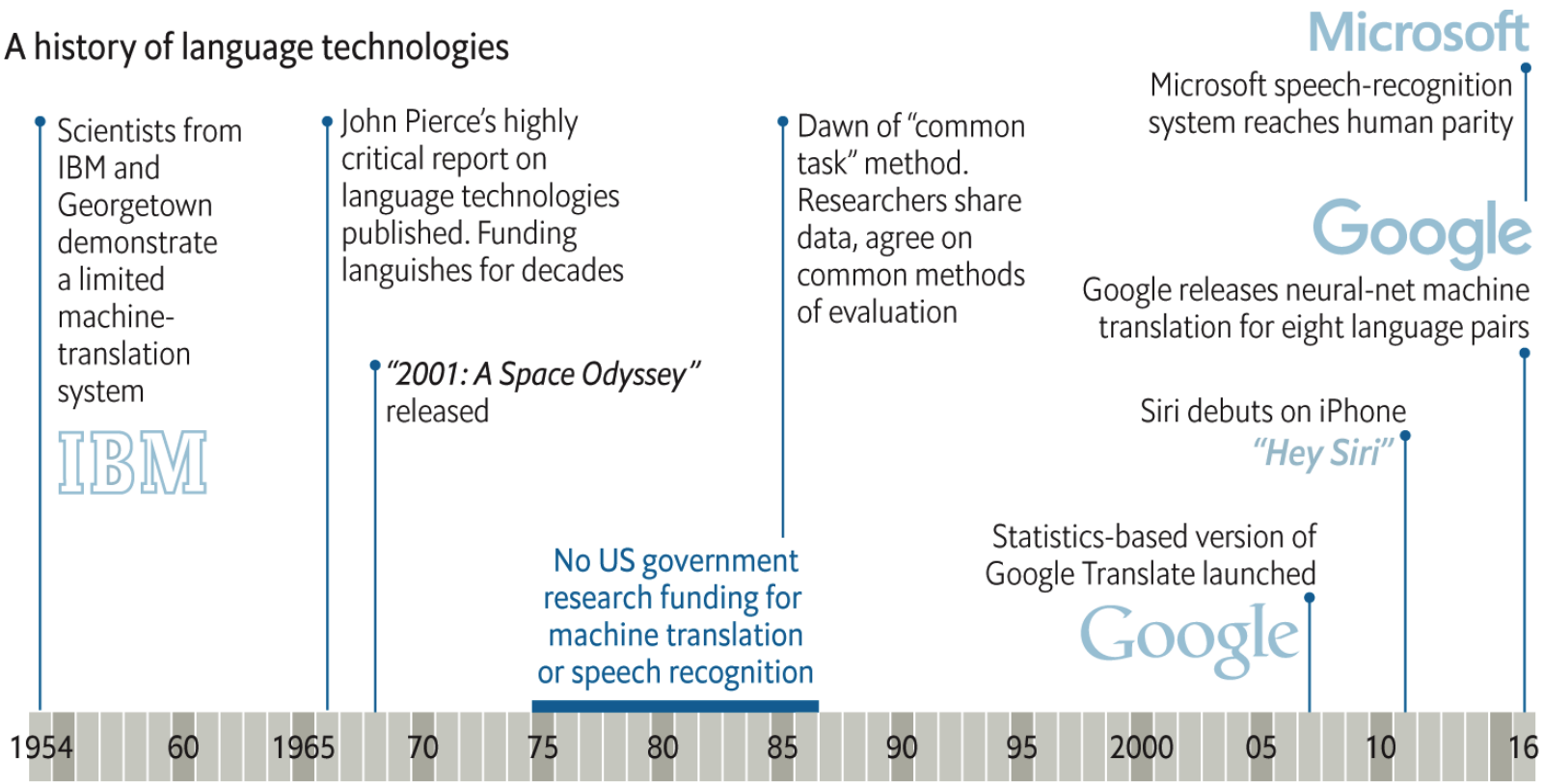
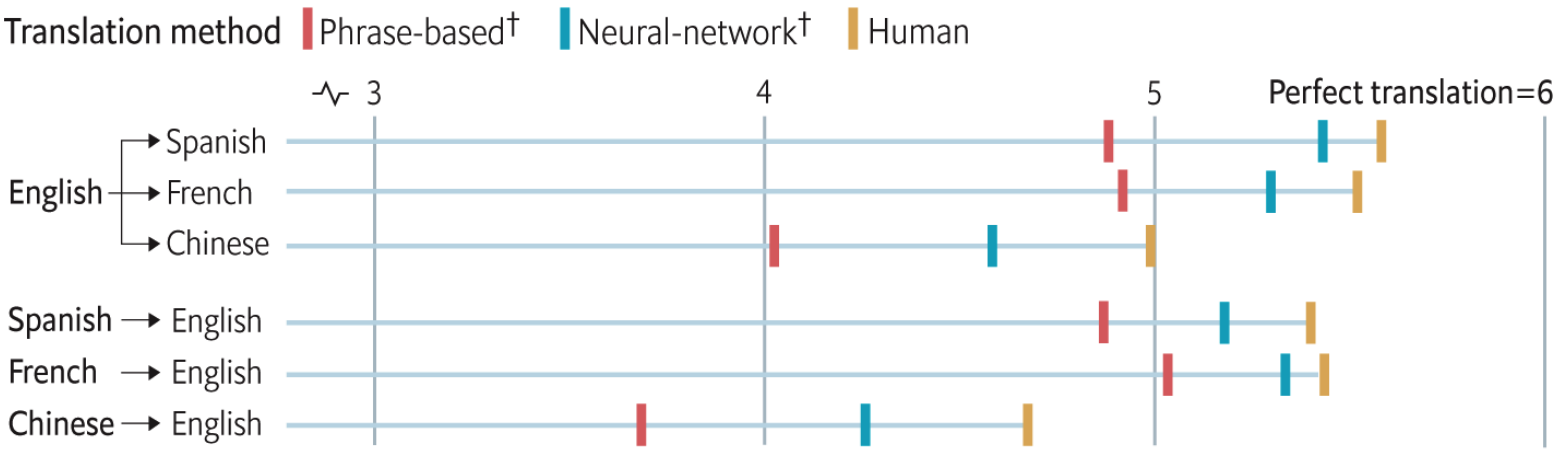




# Sunspring

# Sunspring

INT. SHIP

We see H pull a book from a shelf, flip through it while speaking, and then put it back.

H
In a future with mass unemployment, young people are forced to sell blood. That's the first thing I can do.

H2
You should see the boys and shut up. I was the one who was going to be a hundred years old.

H
I saw him again. The way you were sent to me... that was a big honest idea. I am not a bright light.

C
Well, I have to go to the skull. I don't know.

He picks up a light screen and fights the security force of the particles of a transmission on his face.

H
(continuing)
What do you mean?

C
(smiles)
I don't know anything about any of this.

H
(to Hauk, taking his eyes from his mouth)
Then what?

H2
There's no answer.

C
(frowning)
We're going to see the money.

H
(reading)
"All right, you can't tell me that."

Steps back. Coffey is still going through.

C
I was coming to that thing because you were so pretty.

H
I don't know. I don't know what you're talking about.

C
That's right.

H
So what are you doing?

H2
I don't want to be honest with you.

He looks at him for a moment, then smiles at him.

H
You don't have to be a doctor.

H2
I am not sure. I don't know what you're talking about.

H
I want to see you too.

H2
What do you mean?

He starts to shake.

H
I'm sorry, but I'm sure you wouldn't even touch me.

H2
I don't know what you're talking about.

H
The principle is completely constructed for the same time.

H2
(smiling)
It was all about you to be true.

H
You didn't even see the movie with the rest of the base.

H2
I don't know.

H
I don't care.

H2
I know that it's a consequence. Whatever you want to know about the presence of the story, I'm a little bit of a boy on the floor.

H
I don't know. I just have to ask you to explain to me what you say.

H2
What do you mean?

H
Because I don't know what you're talking about.

H2
That was all the time.

H
I know that.

H2
I don't know.

H
(angry)
It would be a good time. I think I could have been my life.

H (CONT'D)
It may never be forgiven, but that is just too bad. I have to leave, but I'm not free of the world.

C
Yes. Perhaps I should take it from here. I'm not going to do something.

H
You can't afford to take this anywhere. It's not a dream. But I've got a good time to stay there.

C
Well, I think you can still be back on the table.

H
Mmm. It's a damn thing scared to say. Nothing is going to be a thing but I was the one that got on this rock with a child and then I left the other two.

He is standing in the stars and sitting on the floor. He takes a seat on the counter and pulls the camera over to his back. He stares at it. He is on the phone. He cuts the shotgun from the edge of the room and puts it in his mouth. He sees a black hole in the floor leading to the man on the roof.

He comes up behind him to protect him. He is still standing next to him.

He looks through the door and the door closes. He looks at the bag from his backpack, and starts to cry.

T
Well, there's the situation with me and the light on the ship. The guy was trying to stop me. He was like a baby and he was gone. I was worried about him. But even if he would have done it all. He couldn't come any more. I didn't mean to be a virgin. I mean, he was weak. And I thought I'd change my mind. He was crazy to take it out. It was a long time ago. He was a little late. I was going to be a moment. I just wanted to tell you that I was much better than he did. I had to stop him and I couldn't even tell. I didn't want to hurt him. I'm sorry. I know I don't like him. I can go home and be so bad and I love him. So I can get him all the way over here and find the square and go to the game with him and she won't show up. Then I'll check it out. But I'm going to see him when he gets to me. He looks at me and he throws me out of his eyes. Then he said he'd go to bed with me.

# Word Vectors

## word2vec & Vector-Space Embedding

[vse 2000]

[word2viz]

# Recurrent Neural Networks

## GRUs and LSTMs

[BiLSTM notebook]

# Advanced Architectures

[multi-ConvNet notebook]

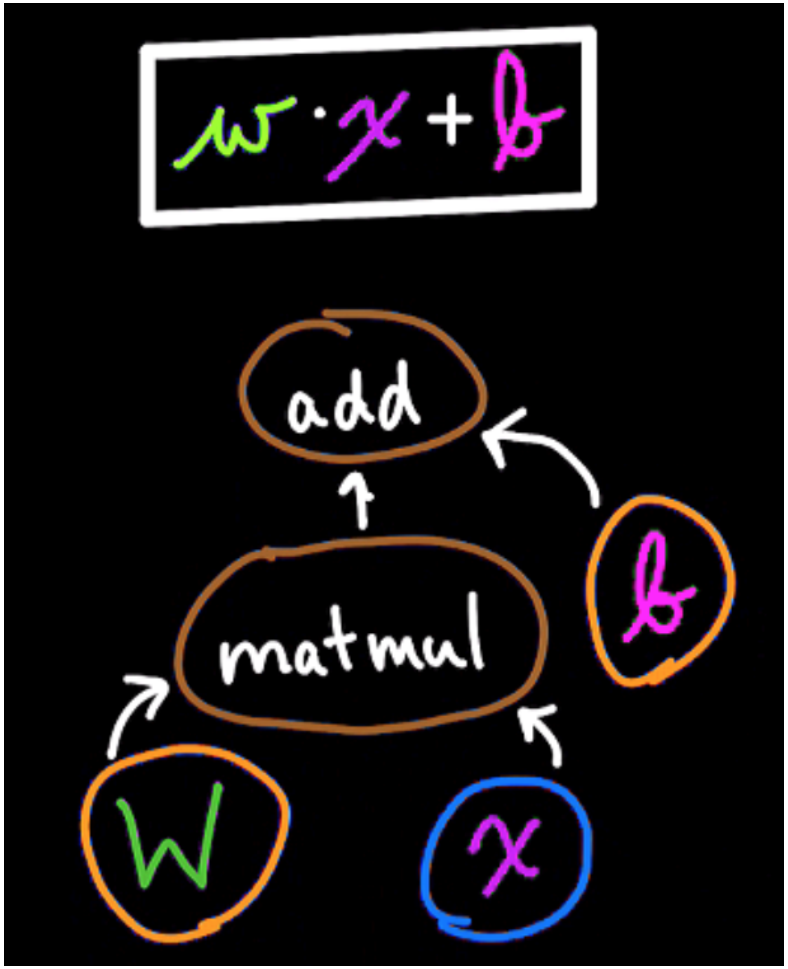
# Your Deep Learning Project III

## Improving

# Outline

# TensorFlow

## Unit 7 & 8: March 24th



# Leading DL Libraries

## A Comparison

| | Caffe | Torch | Theano | TensorFlow |
|---|---|---|---|---|
| *language* | Python, C++ | Lua, PyTorch | Python | Python, Java, C, Go |
| *pre-trained models* | Model Zoo | ModelZoo | Lasagne | Inception, others |
| *parallel GPUs: data* | Yes | Yes | Yes | Yes |
| *parallel GPUs: model* | | Yes | | Yes |
| *source code* | Readable | Readable | | |
| *for RNNs* | | | Good | Best |
| *high-level APIs* | | | Keras | Keras, TFLearn |

# Neurons in TensorFlow

[LeNet-5 in TF]

# Improving Model Performance

1. Xavier Glorot initialization
2. problem simplification
3. layer architecture
4. cost function
5. avoid overfitting
6. variable learning rate $\eta$
7. epochs
8. regularization parameters, e.g., $\lambda$
9. mini-batch size
10. grid-search automation

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# Tuning Hyperparameters

...in `lenet_in_keras.ipynb`:

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(n_classes, activation='softmax'))
```

...in `lenet_in_tensorflow.ipynb`:

```
# max pooling layer:
pool_size = 2
mp_layer_dropout = 0.25

# dense layer:
n_dense = 128
dense_layer_dropout = 0.5
```

```
# convolutional and max-pooling layers:
conv_1 = conv2d(square_x, weights['W_c1'], biases['b_c1'])
conv_2 = conv2d(conv_1, weights['W_c2'], biases['b_c2'])
pool_1 = maxpooling2d(conv_2, mp_psize)
pool_1 = tf.nn.dropout(pool_1, 1-mp_dropout)

# dense layer:
flat = tf.reshape(pool_1, [-1, weights['W_d1'].get_shape().as_list()[0]])
dense_1 = dense(flat, weights['W_d1'], biases['b_d1'])
dense_1 = tf.nn.dropout(dense_1, 1-dense_dropout)
```

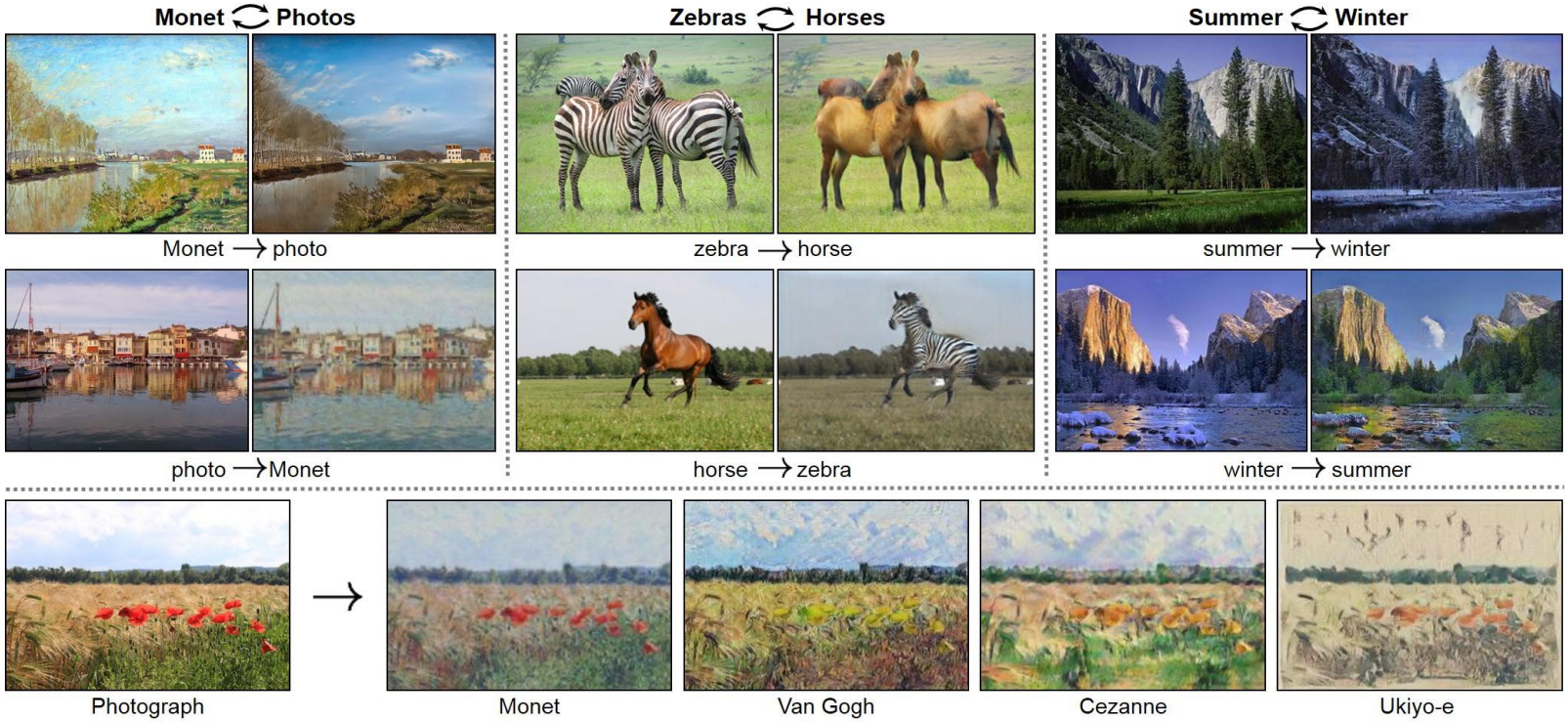
# Your Deep Learning Project IV

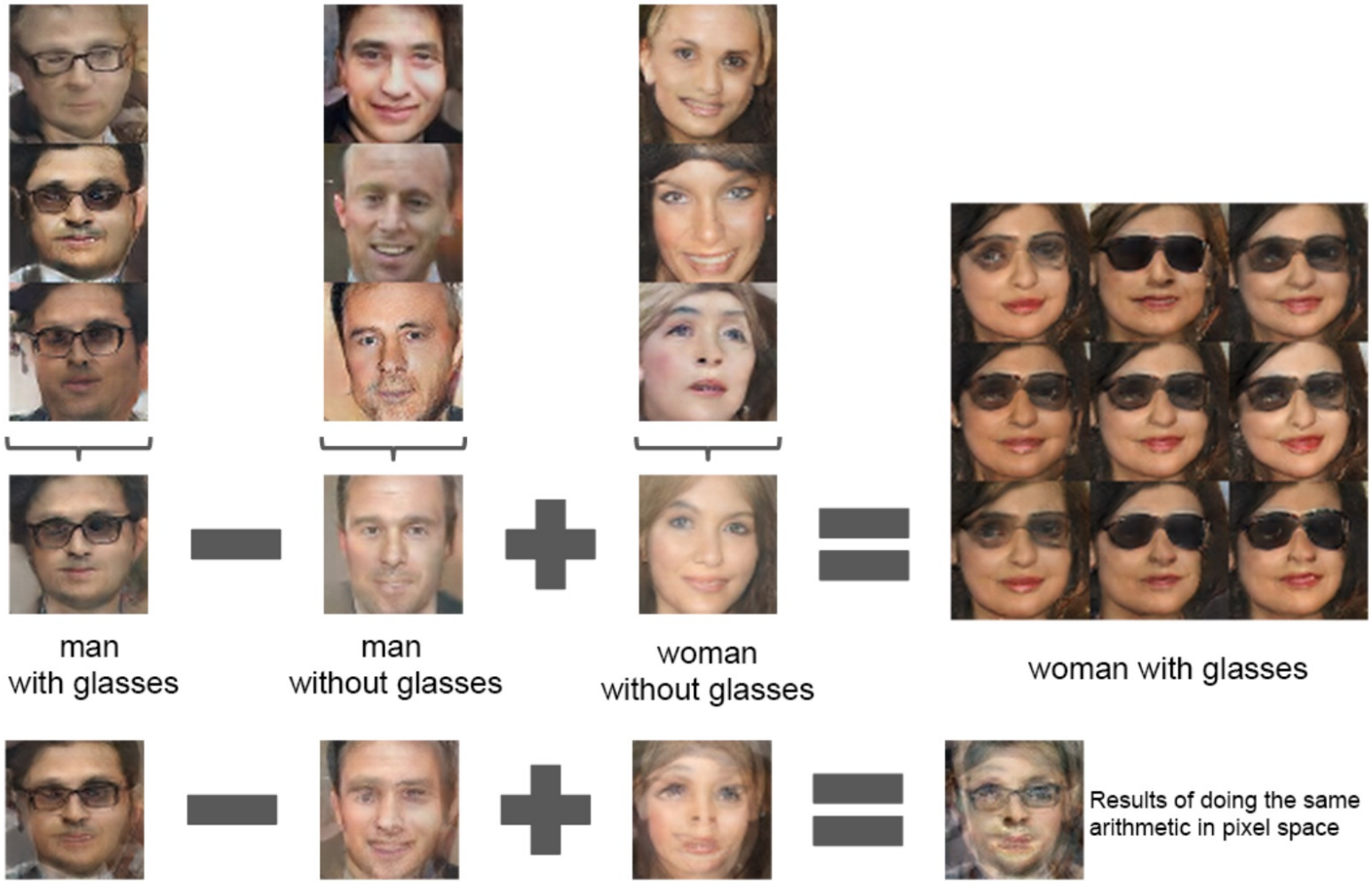
## Assessing

# Generative Adversarial Networks

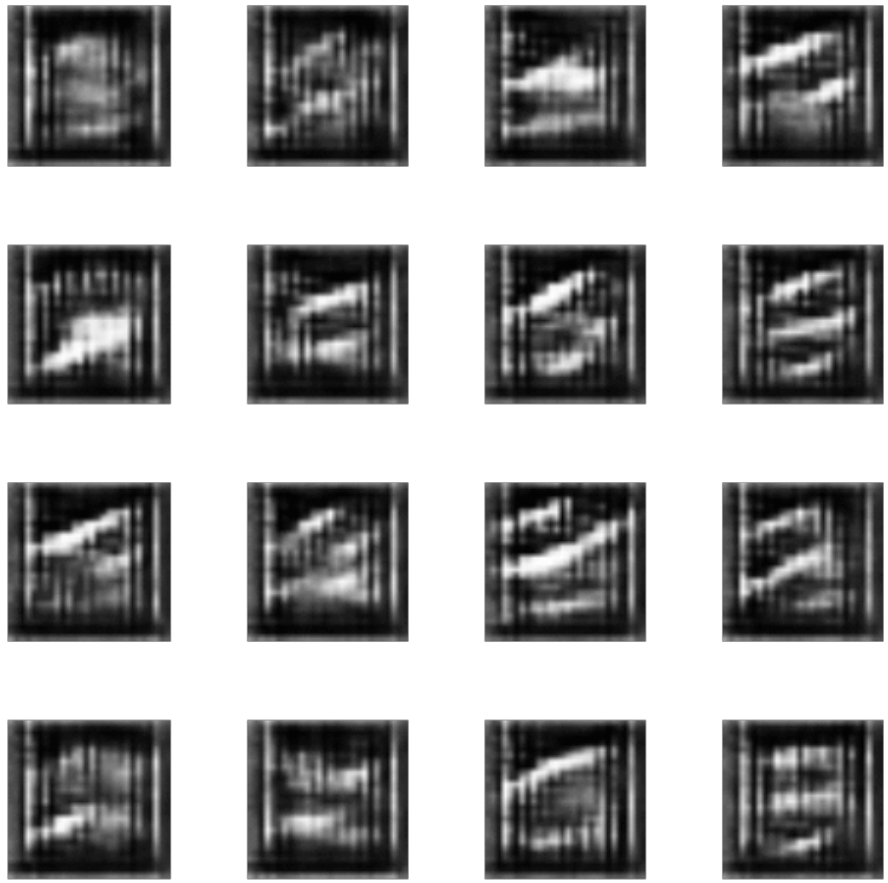
## Unit 9: April 7th AM

NYC DATA SCIENCE ACADEMY





[Quick, Draw!]



[*GAN* notebook]

# Deep Reinforcement Learning

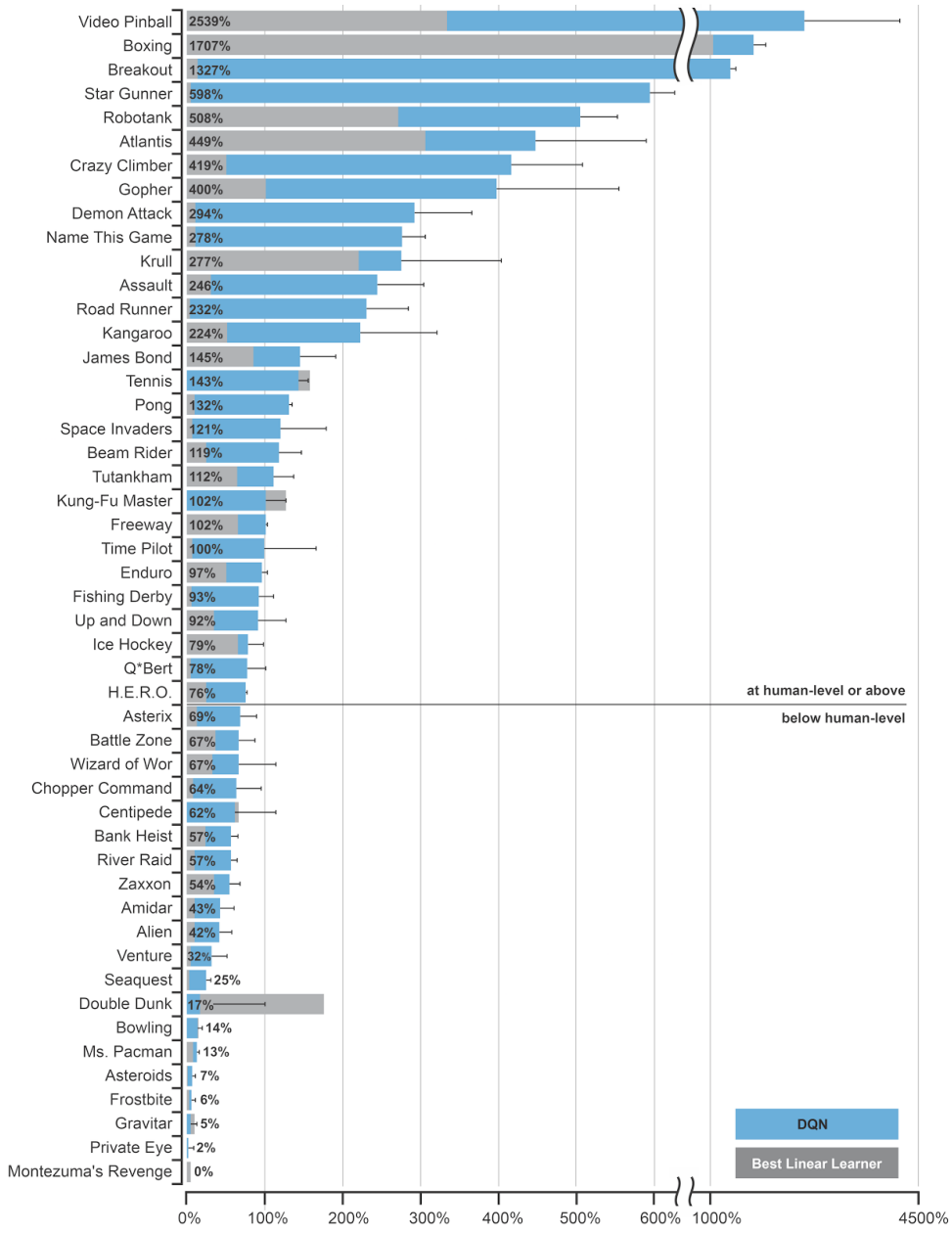
## Unit 10: April 7th PM

# AlphaGO

## Silver et al. (2016)

# Deep Q-Learning

## Mnih et al. (2015)




[Atari Games]

# Deep Q-Learning

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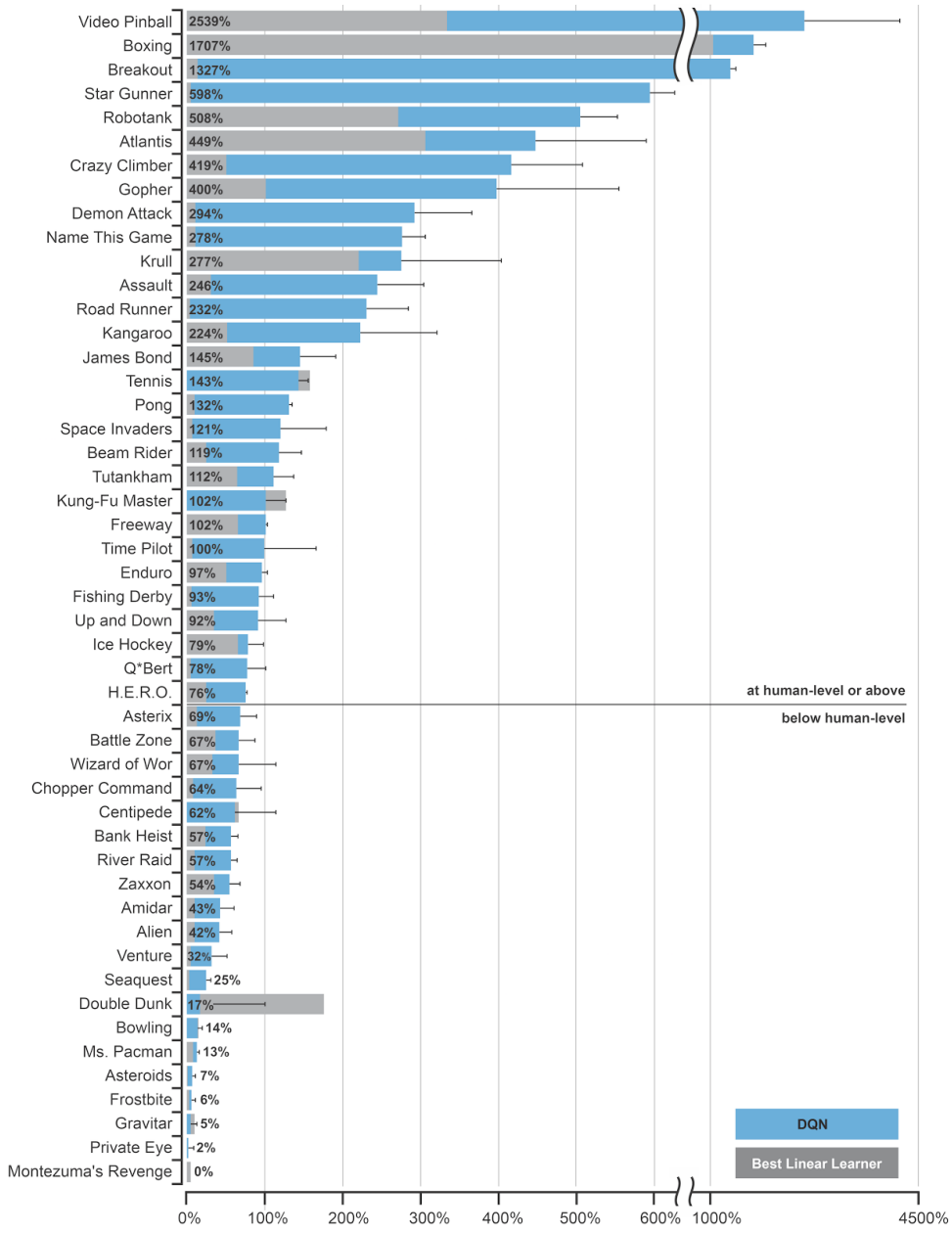


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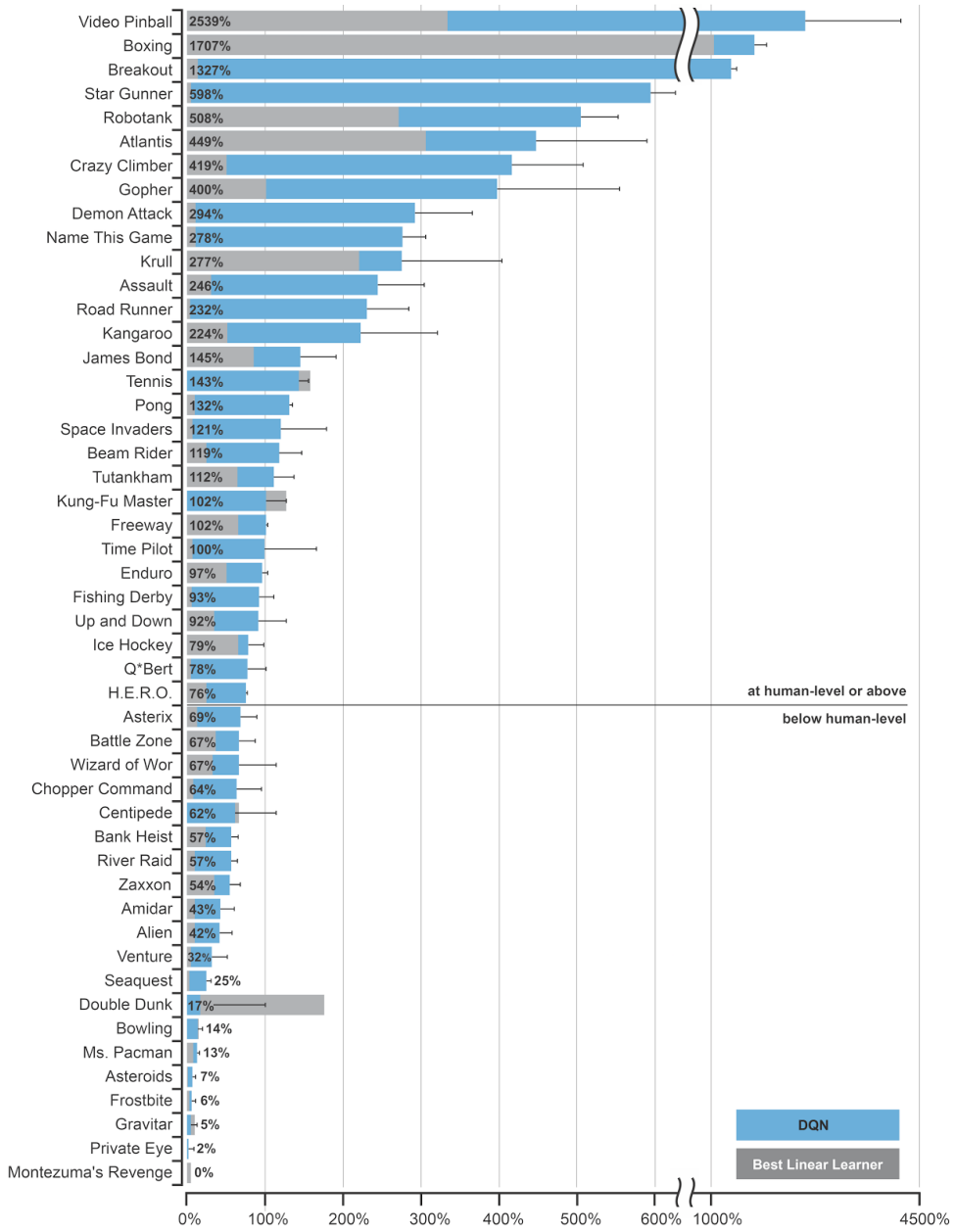


[Atari Games]

[*Deep Q-Learning Network* notebook]

[SLM-Lab]

# Your Deep Learning Project V

## Presentations

# Demand for AI Talent

i.e., *Deep Learning* talent

"Of the ten most valuable quoted companies in the world, seven say they have plans to put deep-learning-based AI at the heart of their operations"

~*The Economist* (Feb. 17th, 2018)

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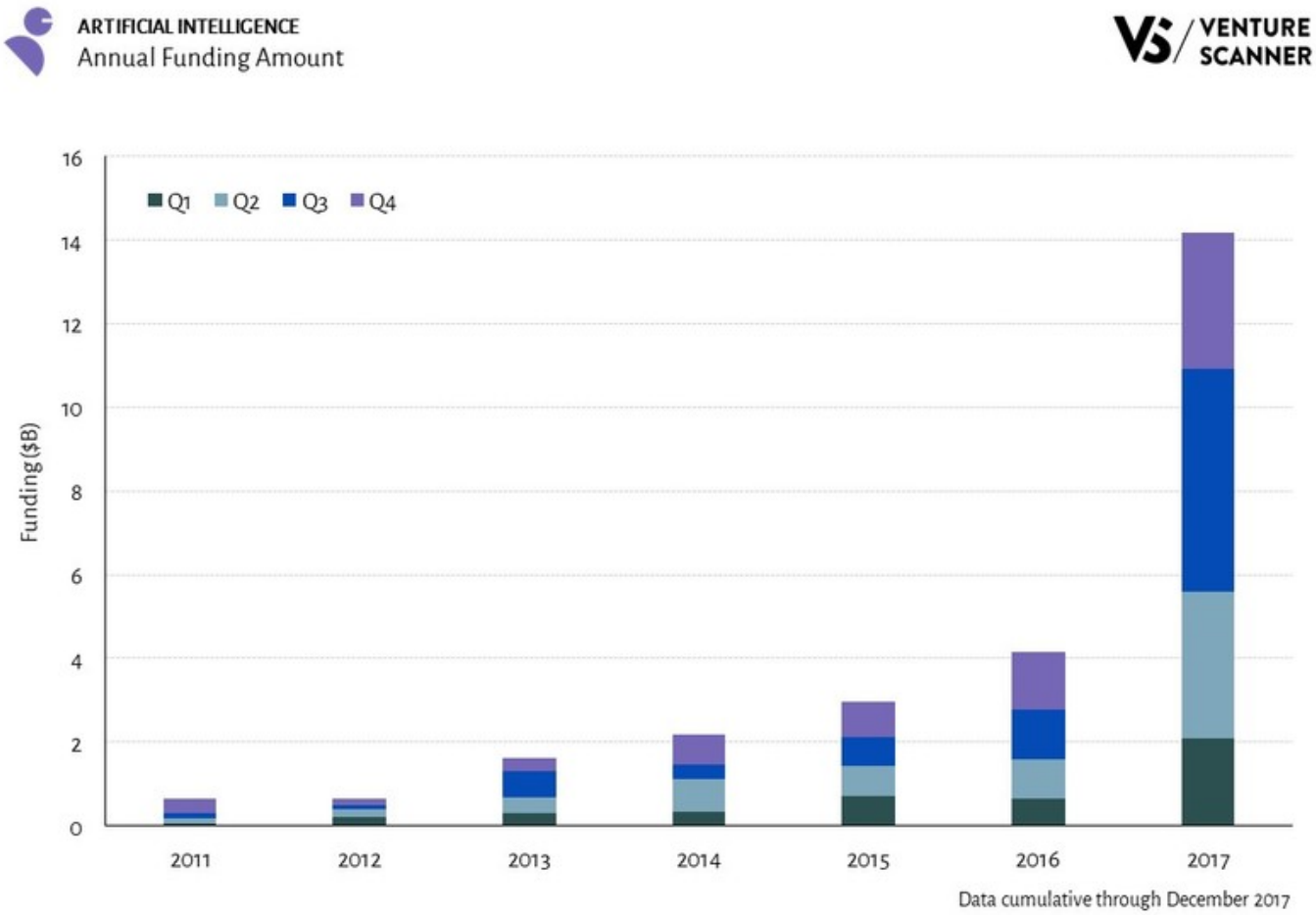
## i.e., *Deep Learning* talent



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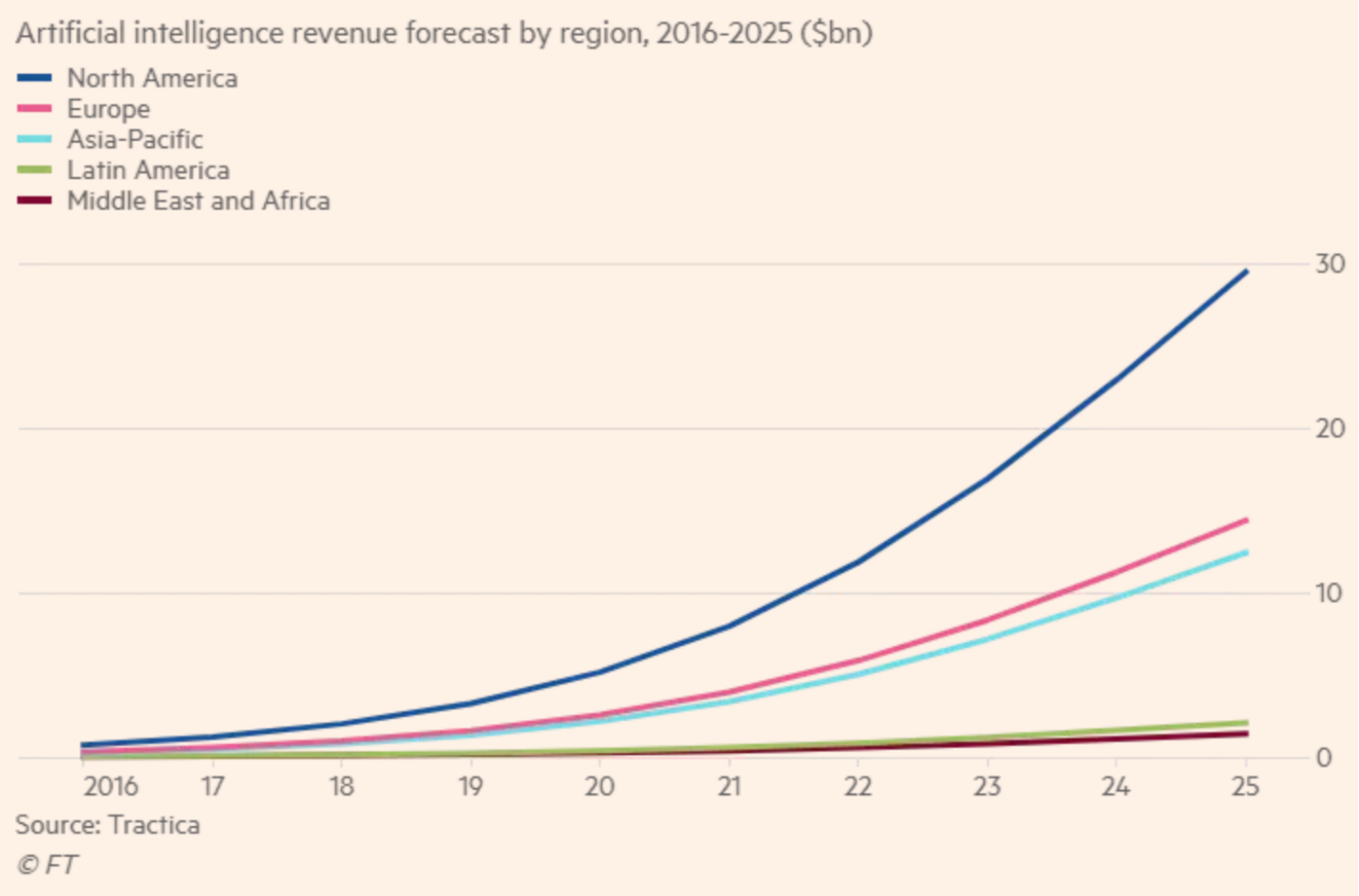

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According to JF Gagne's [Global AI Talent Report 2018]:

1. 22k Ph.D.-educated researchers globally
2. 3k of those currently looking
3. 5k publishing / presenting at AI conferences

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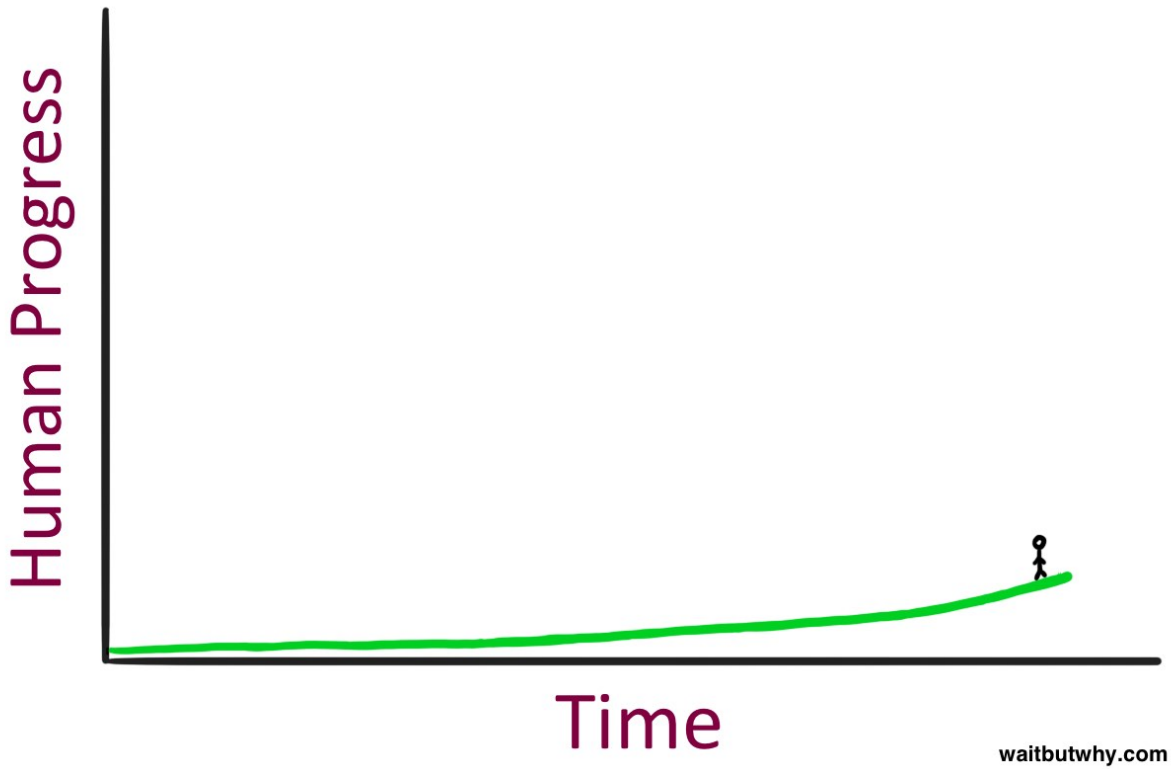
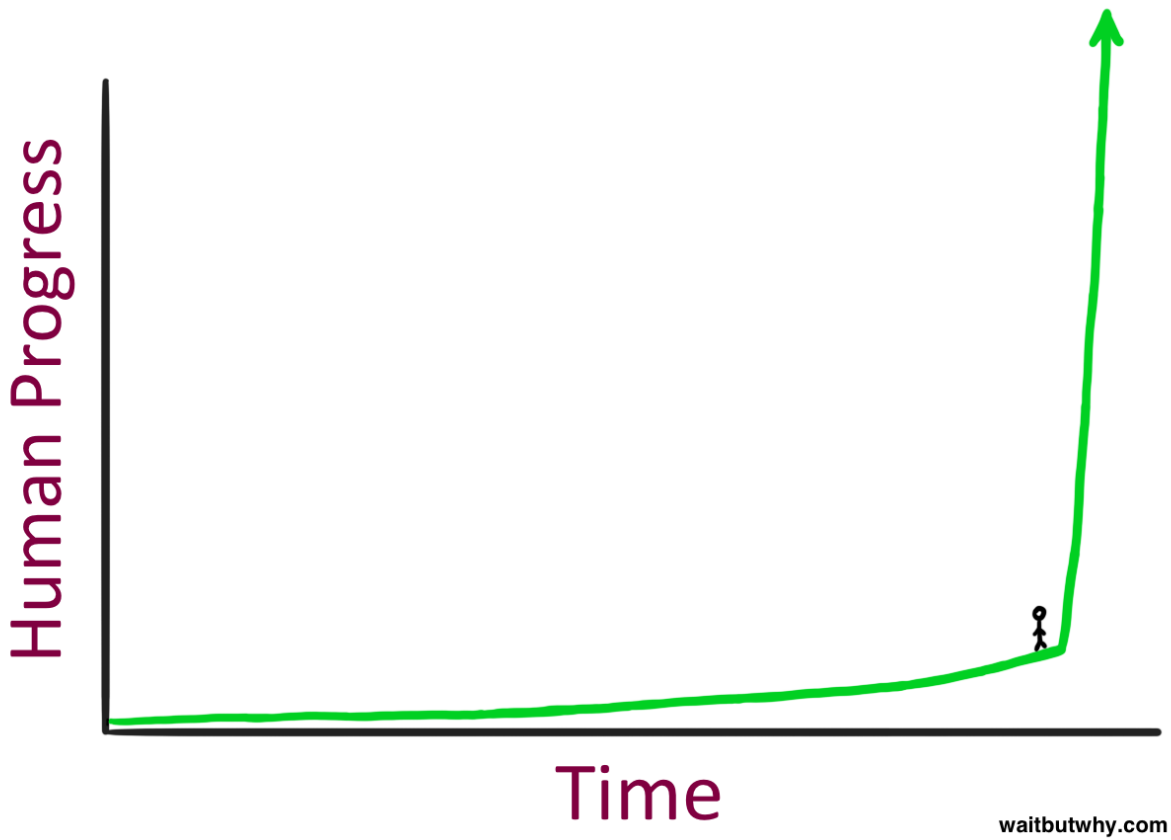
# The AI Revolution



# The AI Revolution



# Outline

# TensorFlow Playground

## Interactive ANN Visualization

[TensorFlow Playground]

# Outline

# Hardware Options for DL

## incl. how to build a DL server

- local machine
- eGPU
- (Tesla K80) cloud instance
- (GTX 1080ti) monster box

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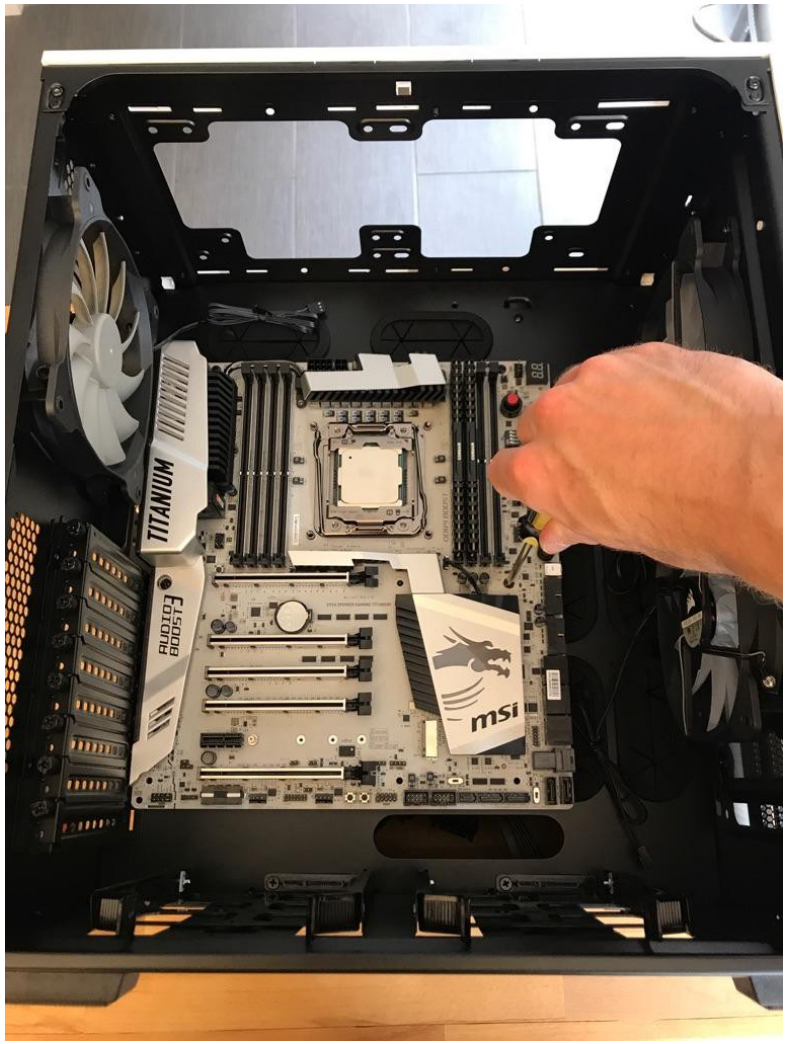
# Local Machine

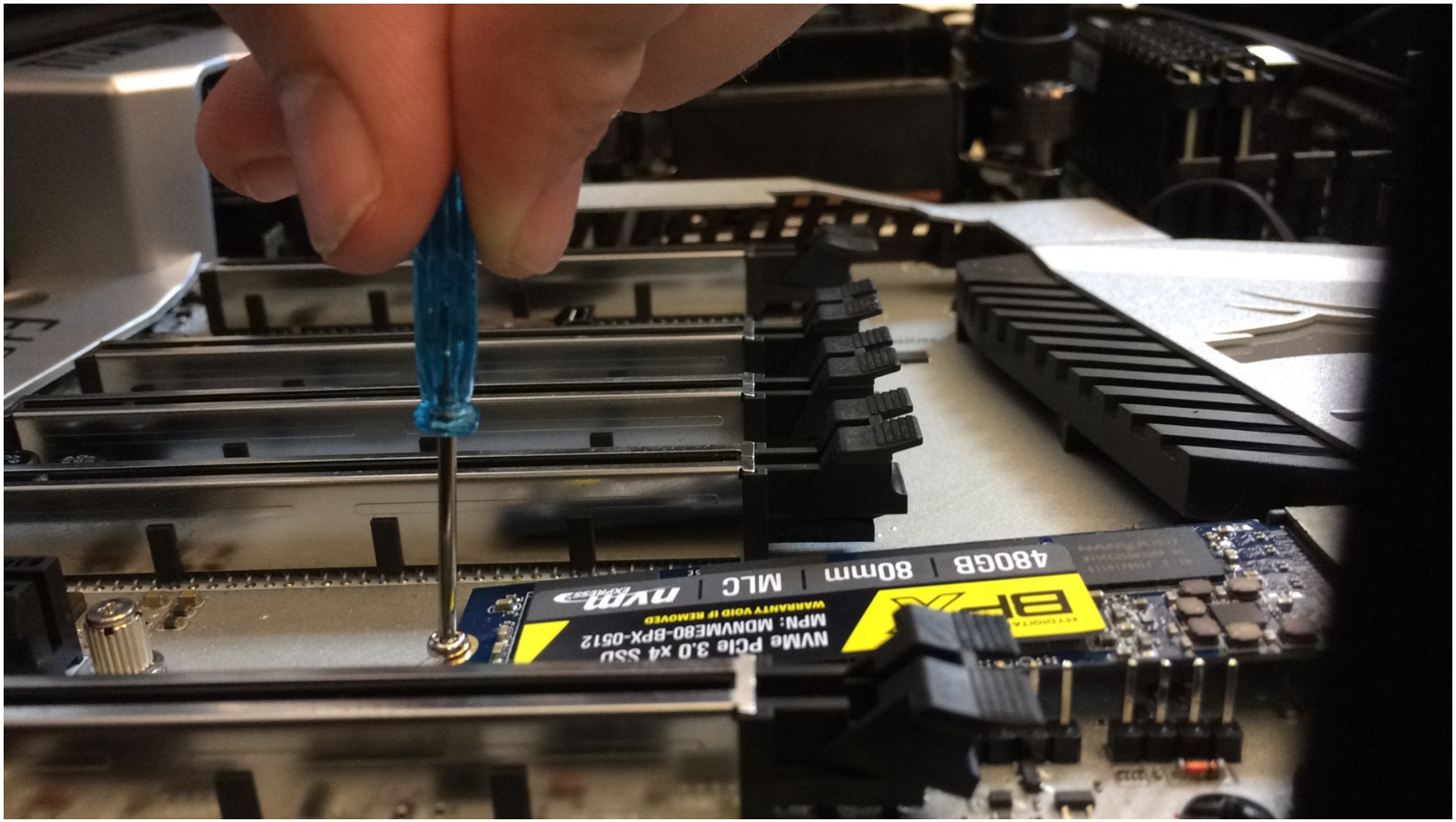
# Remote Cloud Instance

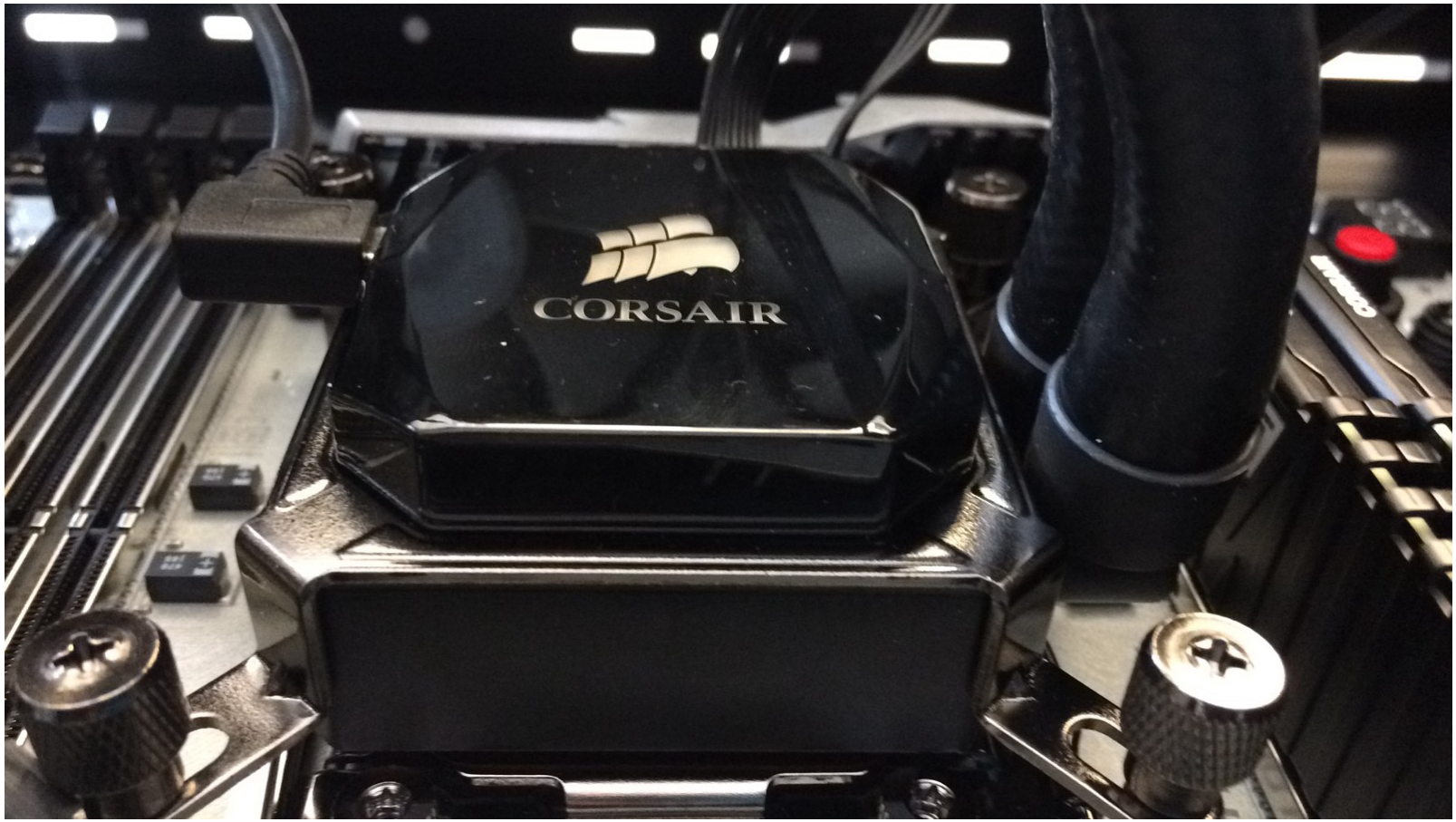
[GCP Ubuntu Instance]

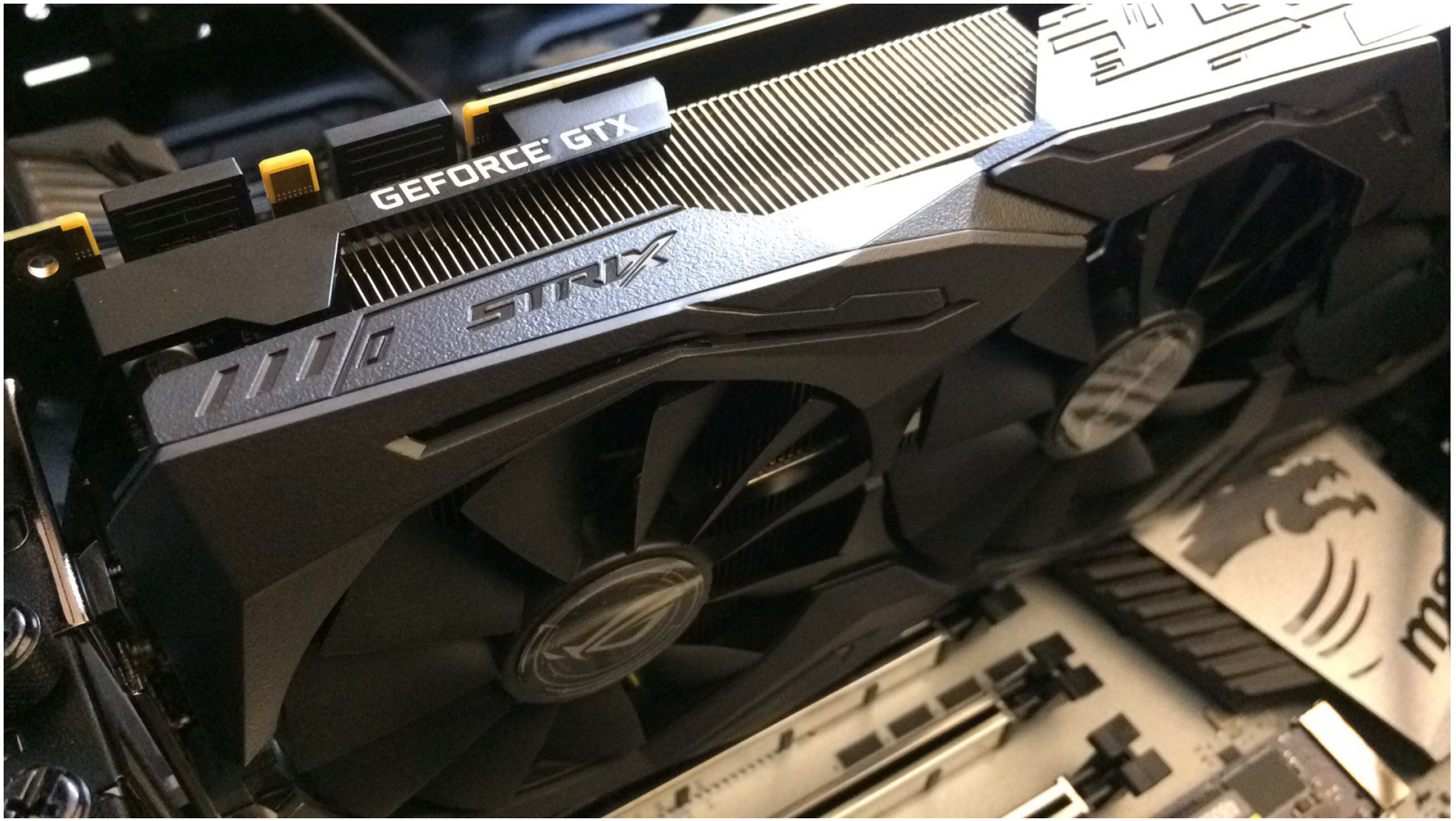
# Build Your Own Monster Box


[PC Part Picker]
[Blog Post]









# Outline

# Software Installation

## How did everyone get on?

[installation instructions]

# Jupyter Notebooks

## + Docker + Nvidia GPU

[Dockerfile]

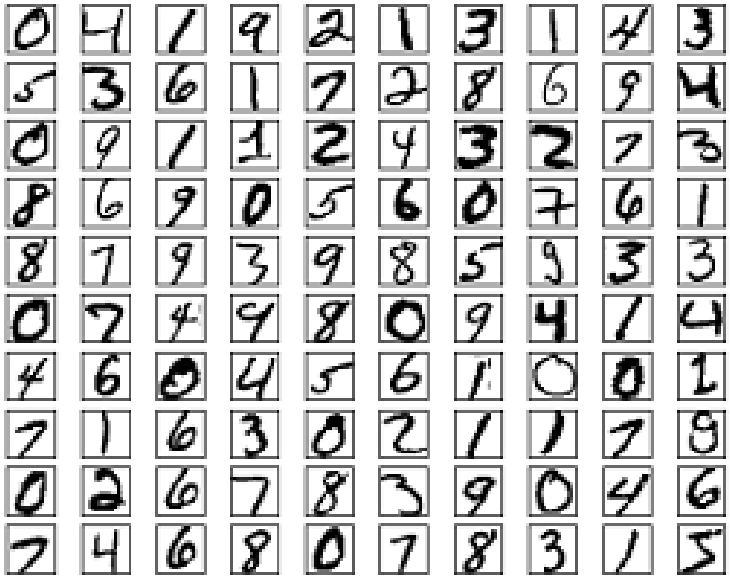
# Jupyter Notebooks

## + Docker + Nvidia GPU + *TensorFlow*

[Dockerfile]

# Outline

# A Shallow Neural Network



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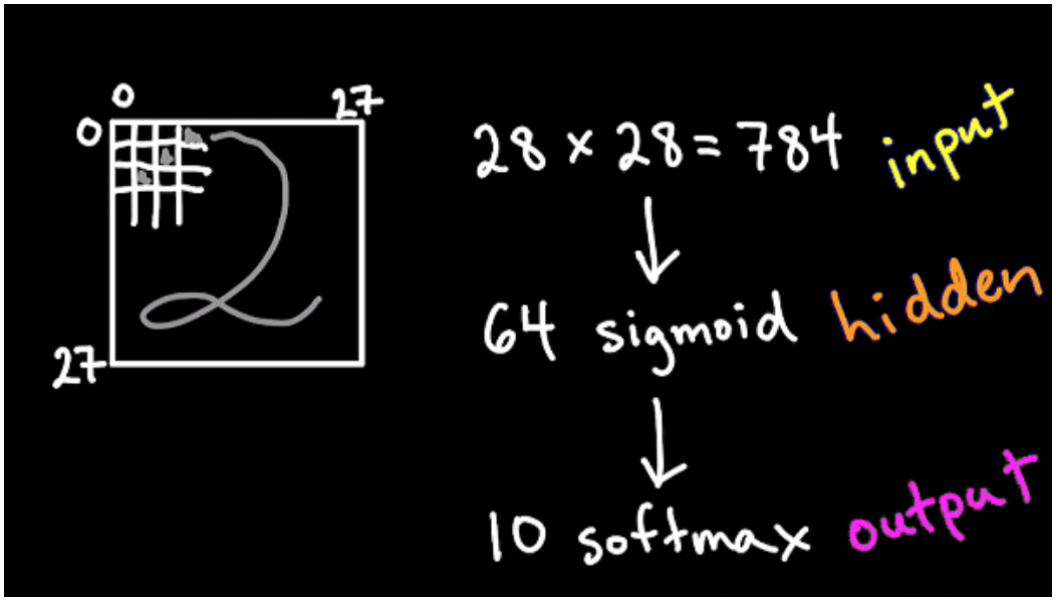


[shallow notebook]